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# Implicit Differentiation for Fast Hyperparameter Selection in Non-Smooth Convex Learning

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## Abstract

Finding the optimal hyperparameters of a model can be cast as a bilevel optimization problem, typically solved using zero-order techniques. In this work we study first-order methods when the inner optimization problem is convex but non-smooth. We show that the forward-mode differentiation of proximal gradient descent and proximal coordinate descent yield sequences of Jacobians converging toward the exact Jacobian. Using implicit differentiation, we show it is possible to leverage the non-smoothness of the inner problem to speed up the computation. Finally, we provide a bound on the error made on the hypergradient when the inner optimization problem is solved approximately. Results on regression and classification problems reveal computational benefits for hyperparameter optimization, especially when multiple hyperparameters are required.

**Keywords:** Convex optimization, hyperparameter optimization, hyperparameter selection, bilevel optimization, Lasso, generalized linear models

## 1. Introduction

Almost all models in machine learning require at least one hyperparameter, the tuning of which drastically affects accuracy. This is the case for many popular estimators, where

Table 1: Examples of non-smooth inner problems as in (1).

Inner problem, $\Phi$	$f(\beta)$	$g_j(\beta_j, \lambda)$	$e^{\lambda_{\max}}$
Lasso	$\frac{1}{2n} \ y - X\beta\ ^2$	$e^\lambda  \beta_j $	$\frac{1}{n} \ X^\top y\ _\infty$
elastic net	$\frac{1}{2n} \ y - X\beta\ ^2$	$e^{\lambda_1}  \beta_j  + \frac{1}{2} e^{\lambda_2} \beta_j^2$	$\frac{1}{n} \ X^\top y\ _\infty$
sparse log. reg.	$\frac{1}{n} \sum_{i=1}^n \ln(1 + e^{-y_i X_i \beta})$	$e^\lambda  \beta_j $	$\frac{1}{2n} \ X^\top y\ _\infty$
dual SVM	$\frac{1}{2} \ (y \odot X)^\top \beta\ ^2 - \sum_{j=1}^p \beta_j$	$\iota_{[0, e^\lambda]}(\beta_j)$	—

the regularization hyperparameter controls the trade-off between a data fidelity term and a regularization term. Such estimators, including Ridge regression (Hoerl and Kennard, 1970), Lasso (Tibshirani, 1996; Chen et al., 1998), elastic net (Zou and Hastie, 2005), sparse logistic regression (Koh et al., 2007), support-vector machine/SVM (Boser et al., 1992; Platt, 1999) are often cast as an optimization problem (Table 1)

$$\hat{\beta}^{(\lambda)} \in \arg \min_{\beta \in \mathbb{R}^p} \Phi(\beta, \lambda) \triangleq f(\beta) + \underbrace{\sum_{j=1}^p g_j(\beta_j, \lambda)}_{\triangleq g(\beta, \lambda)}, \quad (1)$$

with smooth  $f : \mathbb{R}^p \rightarrow \mathbb{R}$  (i.e., with Lipschitz gradient), proper closed convex (possibly non-smooth) functions  $g_j(\cdot, \lambda)$ , and a regularization hyperparameter  $\lambda \in \mathbb{R}^r$ . In the examples of Table 1, the computation of  $f$  involves a design matrix  $X \in \mathbb{R}^{n \times p}$ ; and the cost of computing  $\nabla f(\beta)$  is  $\mathcal{O}(np)$ . In the SVM example, since we consider the dual problem, we chose to reverse the roles of  $n$  and  $p$  to enforce  $\beta \in \mathbb{R}^p$ . We often drop the  $\lambda$  dependency and write  $\hat{\beta}$  instead of  $\hat{\beta}^{(\lambda)}$  when it is clear from context.

For a fixed  $\lambda$ , the issue of solving efficiently Problem (1) has been largely explored. If the functions  $g_j$  are smooth, one can use solvers such as L-BFGS (Liu and Nocedal, 1989), SVRG (Johnson and Zhang, 2013; Zhang et al., 2013), or SAGA (Defazio et al., 2014). When the functions  $g_j$  are non-smooth, Problem (1) can be tackled efficiently with stochastic algorithms (Pedregosa et al., 2017) or using working set methods (Fan and Lv, 2008; Tibshirani et al., 2012) combined with coordinate descent (Tseng and Yun, 2009), see overview by Massias et al. (2020). The question of *model selection*, i.e., how to select the hyperparameter  $\lambda \in \mathbb{R}^r$  (potentially multidimensional), is more open, especially when the dimension  $r$  of the regularization hyperparameter  $\lambda$  is large.

For the Lasso, a broad literature has been devoted to parameter tuning. Under strong hypothesis on the design matrix  $X$ , it is possible to derive guidelines for the setting of the regularization parameter  $\lambda$  (Lounici, 2008; Bickel et al., 2009; Belloni et al., 2011). Unfortunately, these guidelines rely on quantities which are typically unknown in practice, and Lasso users still have to resort to other techniques to select the hyperparameter  $\lambda$ .

A popular approach for hyperparameter selection is *hyperparameter optimization* (Kohavi and John, 1995; Hutter et al., 2015; Feurer and Hutter, 2019): one selects the hyperpa-

Table 2: Examples of outer criteria used for hyperparameter selection.

Criterion	Problem type	Criterion $\mathcal{C}(\beta)$
Hold-out mean squared error	Regression	$\frac{1}{n} \ y^{\text{val}} - X^{\text{val}}\beta\ ^2$
Stein unbiased risk estimate (SURE) <sup>1</sup>	Regression	$\ y - X\beta\ ^2 - n\sigma^2 + 2\sigma^2 \text{dof}(\beta)$
Hold-out logistic loss	Classification	$\frac{1}{n} \sum_{i=1}^n \ln(1 + e^{-y_i^{\text{val}} X_{i:}^{\text{val}} \beta})$
Hold-out smoothed Hinge loss <sup>2</sup>	Classification	$\frac{1}{n} \sum_{i=1}^n \ell(y_i^{\text{val}}, X_{i:}^{\text{val}} \beta)$

parameter  $\lambda$  such that the regression coefficients  $\hat{\beta}^{(\lambda)}$  minimize a given criterion  $\mathcal{C} : \mathbb{R}^p \rightarrow \mathbb{R}$ . Here  $\mathcal{C}$  should ensure good generalization, or avoid overcomplex models. Common examples (see Table 2) include the hold-out loss (Devroye and Wagner, 1979), the cross-validation loss (CV, Stone and Ramer 1965, see Arlot and Celisse 2010 for a survey), the AIC (Akaike, 1974), BIC (Schwarz, 1978) or SURE (Stein, 1981) criteria. Formally, the hyperparameter optimization problem is a bilevel optimization problem (Colson et al., 2007)

$$\begin{aligned} & \arg \min_{\lambda \in \mathbb{R}^r} \left\{ \mathcal{L}(\lambda) \triangleq \mathcal{C}(\hat{\beta}^{(\lambda)}) \right\} \\ & \text{s.t. } \hat{\beta}^{(\lambda)} \in \arg \min_{\beta \in \mathbb{R}^p} \Phi(\beta, \lambda) . \end{aligned} \quad (2)$$

Popular approaches to solve (the generally non-convex) Problem (2) include zero-order optimization (gradient-free) techniques such as grid-search, random-search (Rastrigin, 1963; Bergstra and Bengio, 2012; Bergstra et al., 2013) or Sequential Model-Based Global Optimization (SMBO), often referred to as Bayesian optimization (Mockus, 1989; Jones et al., 1998; Forrester et al., 2008; Brochu et al., 2010; Snoek et al., 2012). Grid-search is a naive discretization of Problem (2). It consists in evaluating the outer function  $\mathcal{L}$  on a grid of hyperparameters, solving one inner optimization Problem (1) for each  $\lambda$  in the grid (see Figure 1). For each inner problem solution  $\hat{\beta}^{(\lambda)}$ , the criterion  $\mathcal{C}(\hat{\beta}^{(\lambda)})$  is evaluated, and the model achieving the lowest value is selected. Random-search has a similar flavor, but one randomly selects where the criterion must be evaluated. Finally, SMBO models the objective function  $\mathcal{L}$  via a function amenable to uncertainty estimates on its predictions such as a Gaussian process. Hyperparameter values are chosen iteratively to maximize a function such as the expected improvement as described, *e.g.*, by Bergstra et al. (2011). However, these zero-order methods share a common drawback: they scale exponentially with the dimension of the search space (Nesterov, 2004, Sec. 1.1.2).

When the hyperparameter space is continuous and the regularization path  $\lambda \mapsto \hat{\beta}^{(\lambda)}$  is well-defined and almost everywhere differentiable, first-order optimization methods are well suited to solve the bilevel optimization Problem (2). Using the chain rule, the gradient of

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1. For a linear model  $y = X\beta + \varepsilon$ , with  $\varepsilon \sim \mathcal{N}(0, \sigma^2)$ , the degree of freedom (dof, Efron 1986) is defined as  $\text{dof}(\beta) = \sum_{i=1}^n \text{cov}(y_i, (X\beta)_i) / \sigma^2$ .
  2. The smoothed Hinge loss is given by  $\ell(x) = \frac{1}{2} - x$  if  $x \leq 0$ ,  $\frac{1}{2}(1 - x)^2$  if  $0 \leq x \leq 1$  and 0 else.

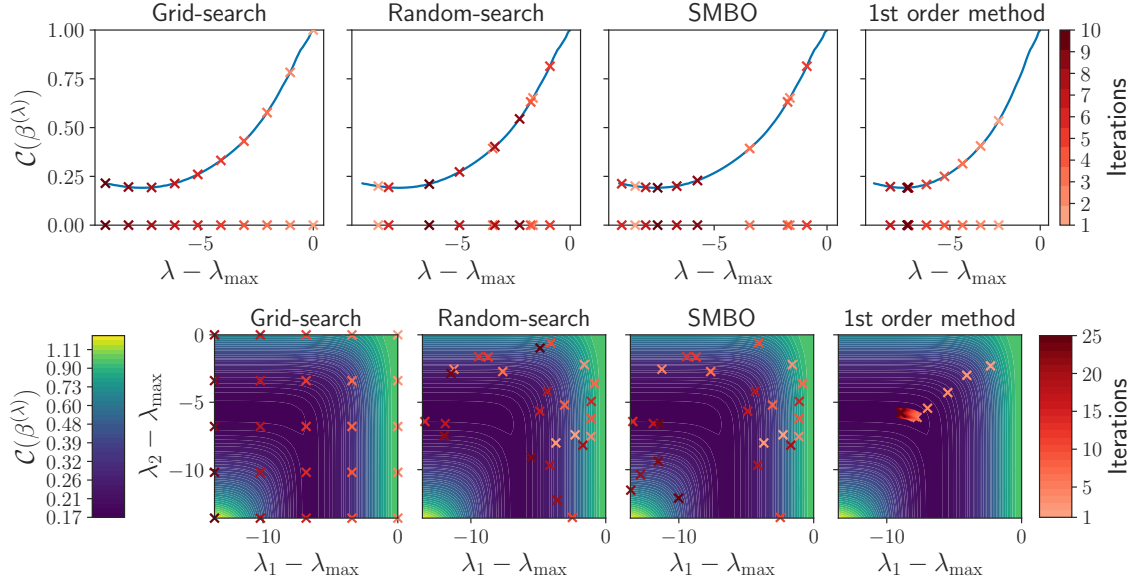


Figure 1: 5-fold cross-validation error  $\mathcal{C}(\beta^{(\lambda)})$ : (top) Lasso CV error with respect to  $\lambda$  for multiple hyperparameter optimization methods on the *real-sim* data set, and (bottom) elastic net CV error with respect to  $\lambda_1$  and  $\lambda_2$  on the *rcv1* data set. Crosses represent the 10 (top) or 25 (bottom) first error evaluations for each method.

$\mathcal{L}$  with respect to  $\lambda$ , also referred to as the *hypergradient*, evaluates to

$$\nabla_{\lambda} \mathcal{L}(\lambda) = \hat{\mathcal{J}}_{(\lambda)}^{\top} \nabla \mathcal{C}(\hat{\beta}^{(\lambda)}) , \quad (3)$$

with  $\hat{\mathcal{J}}_{(\lambda)} \in \mathbb{R}^{p \times r}$  the *Jacobian* of the function  $\lambda \mapsto \hat{\beta}^{(\lambda)}$ ,

$$\hat{\mathcal{J}}_{(\lambda)} \triangleq \begin{pmatrix} \frac{\partial \hat{\beta}_1^{(\lambda)}}{\partial \lambda_1} & \cdots & \frac{\partial \hat{\beta}_1^{(\lambda)}}{\partial \lambda_r} \\ \vdots & \cdots & \vdots \\ \frac{\partial \hat{\beta}_p^{(\lambda)}}{\partial \lambda_1} & \cdots & \frac{\partial \hat{\beta}_p^{(\lambda)}}{\partial \lambda_r} \end{pmatrix} . \quad (4)$$

An important challenge of applying first-order methods to solve [Problem \(2\)](#) is evaluating the hypergradient in [Equation \(3\)](#). There are three main algorithms to compute the hypergradient  $\nabla_{\lambda} \mathcal{L}(\lambda)$ : implicit differentiation ([Larsen et al., 1996](#); [Bengio, 2000](#)) and automatic differentiation using the reverse-mode ([Linnainmaa, 1970](#); [LeCun et al., 1998](#)) or the forward-mode ([Wengert, 1964](#); [Deledalle et al., 2014](#); [Franceschi et al., 2017](#)). As illustrated in [Figure 1](#), once the hypergradient in [Equation \(3\)](#) has been computed, one can solve [Problem \(2\)](#) with first-order schemes, *e.g.*, gradient descent.

*Contributions.* We are interested in tackling the bilevel optimization [Problem \(2\)](#), with a non-smooth inner optimization [Problem \(1\)](#). More precisely,

- We show that classical algorithms used to compute hypergradients for smooth inner problem have theoretically grounded non-smooth counterparts. We provide in [Theorem 9](#) an implicit differentiation formula for non-smooth optimization problems. We obtain in [Theorem 13](#), for the first time in the non-smooth case, error bounds with respect to the hypergradient when the inner problem and the linear system involved are only solved approximately. We obtain in [Theorem 12](#) convergence rates on the hypergradient for iterative differentiation of non-smooth optimization problems.
- Based on the former contributions we propose an algorithm to tackle [Problem \(2\)](#). We develop an efficient implicit differentiation algorithm to compute the hypergradient in [Equation \(3\)](#), leveraging the sparsity of the Jacobian and enabling the use of state-of-the-art solvers ([Algorithm 5](#)). We combine in [Algorithm 6](#) this fast hypergradient computation with a gradient descent scheme to solve [Problem \(2\)](#).
- We provide extensive experiments on diverse data sets and estimators ([Section 4](#)). We first show that implicit differentiation significantly outperforms other hypergradient methods ([Section 4.1](#)). Then, leveraging sparsity, we illustrate computational benefits of first-order optimization with respect to zero-order techniques for solving [Problem \(2\)](#) on Lasso, elastic net and multiclass logistic regression ([Section 4.2](#)).
- We release our implementation as a high-quality, documented and tested Python package: <https://github.com/qb3/sparse-ho>.

*General notation.* We write  $\|\cdot\|$  the Euclidean norm on vectors. For a set  $S$ , we denote by  $S^c$  its complement. We denote  $[p] = \{1, \dots, p\}$ . We denote by  $(e_j)_{j=1}^p$  the vectors of the canonical basis of  $\mathbb{R}^p$ . We denote the coordinate-wise multiplication of two vectors  $u$  and  $v$  by  $u \odot v$ , and by  $u \odot M$  the row-wise multiplication between a vector and a matrix. The  $i$ -th line of the matrix  $M$  is  $M_{i:}$  and its  $j$ -th column is  $M_{:j}$ . The spectral radius of a matrix  $M \in \mathbb{R}^{n \times n}$  is denoted  $\rho(M) = \max_i |s_i|$  where  $s_1, \dots, s_n$  are the eigenvalues of  $M$ . For a matrix  $M$ , we write that  $M \succ 0$  if  $M$  is positive definite. The regularization parameter, possibly multivariate, is denoted by  $\lambda = (\lambda_1, \dots, \lambda_r)^\top \in \mathbb{R}^r$ . Recall that for a locally integrable function  $f : x \in \Omega \mapsto \mathbb{R}$ , where  $\Omega$  is an open subset of  $\mathbb{R}^n$ , its weak partial derivative ([Evans and Gariepy, 1992](#)) with respect to  $x_i$  in  $\Omega$  is the locally integrable function  $g_i$  on  $\Omega$  such that

$$\int_{\Omega} g_i(x) \phi(x) dx = - \int_{\Omega} f(x) \frac{\partial \phi(x)}{\partial x_i} dx, \quad (5)$$

holds for all functions  $\phi$  that are continuously differentiable and of compact support. For vector valued function  $f$ , we denote by  $\mathcal{J}(x)$  its weak Jacobian *i.e.*, the matrix composed of weak partial derivatives. An important use of this notation in the rest of the paper is  $\hat{\mathcal{J}}_{(\lambda)} \triangleq (\nabla_{\lambda} \hat{\beta}_1^{(\lambda)}, \dots, \nabla_{\lambda} \hat{\beta}_p^{(\lambda)})^\top \in \mathbb{R}^{p \times r}$  the weak Jacobian of  $\hat{\beta}^{(\lambda)}$  with respect to  $\lambda$ . *Convex analysis.* For a convex function  $h : \mathbb{R}^p \rightarrow \mathbb{R}$ , the proximal operator of  $h$  is defined, for

Table 3: Partial derivatives of proximal operators used.

$g_j(\beta_j, \lambda)$	$\text{prox}_{g_j(\cdot, \lambda)}(z_j)$	$\partial_z \text{prox}_{g_j(\cdot, \lambda)}(z_j)$	$\partial_\lambda \text{prox}_{g_j(\cdot, \lambda)}(z_j)$
$e^\lambda \beta_j^2 / 2$	$z_j / (1 + e^\lambda)$	$1 / (1 + e^\lambda)$	$-z_j e^\lambda / (1 + e^\lambda)^2$
$e^\lambda  \beta_j $	$\text{ST}(z_j, e^\lambda)$	$ \text{sign}(\text{ST}(z_j, e^\lambda)) $	$-e^\lambda \text{sign}(\text{ST}(z_j, e^\lambda))$
$e^{\lambda_1}  \beta_j  + \frac{1}{2} e^{\lambda_2} \beta_j^2$	$\frac{\text{ST}(z_j, e^{\lambda_1})}{1 + e^{\lambda_2}}$	$\frac{ \text{sign}(\text{ST}(z_j, e^{\lambda_1})) }{1 + e^{\lambda_2}}$	$\left( \frac{-e^{\lambda_1} \text{sign}(\text{ST}(z_j, e^{\lambda_1}))}{1 + e^{\lambda_2}}, \frac{-\text{ST}(z_j, e^{\lambda_1}) e^{\lambda_2}}{(1 + e^{\lambda_2})^2} \right)$
$\iota_{[0, e^\lambda]}(\beta_j)$	$\max(0, \min(z_j, e^\lambda))$	$\mathbb{1}_{]0, e^\lambda[}(z_j)$	$e^\lambda \mathbb{1}_{z_j > e^\lambda}$

any  $x \in \mathbb{R}^p$ , as:  $\text{prox}_h(x) = \arg \min_{y \in \mathbb{R}^p} \frac{1}{2} \|x - y\|^2 + h(y)$ . The subdifferential of  $h$  at  $x$  is denoted  $\partial h(x) = \{u \in \mathbb{R}^p : \forall z \in \mathbb{R}^p, h(z) \geq h(x) + u^\top(z - x)\}$ . A function is said to be *smooth* if it has Lipschitz gradients. Let  $f$  be a  $L$ -smooth function. Lipschitz constants of the functions  $\nabla_j f$  are denoted by  $L_j$ ; hence for all  $x \in \mathbb{R}^p$ ,  $h \in \mathbb{R}$

$$|\nabla_j f(x + h e_j) - \nabla_j f(x)| \leq L_j |h| .$$

For a function  $f$ , its gradient restricted to the indices in a set  $S$  is denoted  $\nabla_S f$ . For a set  $\Xi \subset \mathbb{R}^p$ , its relative interior is noted  $\text{ri}(\Xi)$ , and its indicator function is defined for any  $x \in \mathbb{R}^p$  by  $\iota_\Xi(x) = 0$  if  $x \in \Xi$  and  $+\infty$  otherwise. A function  $h : \mathbb{R} \rightarrow \mathbb{R} \cup \{+\infty\}$  is said to be proper if  $\text{dom}(h) = \{x \in \mathbb{R} : h(x) < +\infty\} \neq \emptyset$ , and closed if for any  $\alpha \in \mathbb{R}$ , the sublevel set  $\{x \in \text{dom}(h) : h(x) \leq \alpha\}$  is a closed set.

For a function  $\psi : \mathbb{R}^p \times \mathbb{R}^r \mapsto \mathbb{R}^p$ , we denote  $\partial_z \psi$  the weak Jacobian with respect to the first variable and  $\partial_\lambda \psi$  the weak Jacobian with respect to the second variable. The proximal operator of  $g(\cdot, \lambda)$  can be seen as such a function  $\psi$  of  $\beta$  and  $\lambda$  (see Table 1 for examples)

$$\begin{aligned} \mathbb{R}^p \times \mathbb{R}^r &\rightarrow \mathbb{R}^p \\ (z, \lambda) &\mapsto \text{prox}_{g(\cdot, \lambda)}(z) = \psi(z, \lambda) . \end{aligned}$$

In this case we denote  $\partial_z \text{prox}_{g(\cdot, \lambda)} \triangleq \partial_z \psi$  and  $\partial_\lambda \text{prox}_{g(\cdot, \lambda)} \triangleq \partial_\lambda \psi$ . Since we consider only separable penalties  $g(\cdot, \lambda)$ ,  $\partial_z \text{prox}_{g(\cdot, \lambda)}$  is a diagonal matrix, so to make notation lighter, we write  $\partial_z \text{prox}_{g(\cdot, \lambda)}$  for its diagonal. We thus have

$$\begin{aligned} \partial_z \text{prox}_{g(\cdot, \lambda)} &= (\partial_z \text{prox}_{g_j(\cdot, \lambda)})_{j \in [p]} \in \mathbb{R}^p \quad (\text{by separability of } g) \\ \partial_\lambda \text{prox}_{g(\cdot, \lambda)} &\in \mathbb{R}^{p \times r} . \end{aligned}$$

Explicit partial derivatives formulas for usual proximal operators can be found in Table 3.

## 2. Related Work

The main challenge to evaluate the hypergradient  $\nabla_\lambda \mathcal{L}(\lambda)$  is the computation of the Jacobian  $\mathcal{J}_{(\lambda)}$ . We first focus on the case where  $\Phi(\cdot, \lambda)$  is convex and smooth for any  $\lambda$ .



*Implicit differentiation.* We recall how the *implicit differentiation*<sup>3</sup> formula of the gradient  $\nabla_\lambda \mathcal{L}(\lambda)$  is obtained for smooth inner optimization problems. We will provide a generalization to non-smooth optimization problems in [Section 3.2](#).

**Theorem 1** ([Bengio, 2000](#)). *Let  $\hat{\beta}^{(\lambda)} \in \arg \min_{\beta \in \mathbb{R}^p} \Phi(\beta, \lambda)$  be a solution of [Problem \(1\)](#). Assume that for all  $\lambda > 0$ ,  $\Phi(\cdot, \lambda)$  is a convex smooth function,  $\nabla_\beta^2 \Phi(\hat{\beta}^{(\lambda)}, \lambda) \succ 0$ , and that for all  $\beta \in \mathbb{R}^p$ ,  $\Phi(\beta, \cdot)$  is differentiable over  $]0, +\infty[$ . Then the hypergradient  $\nabla_\lambda \mathcal{L}(\lambda)$  reads*

$$\underbrace{\nabla_\lambda \mathcal{L}(\lambda)}_{\in \mathbb{R}^r} = \underbrace{-\nabla_{\beta, \lambda}^2 \Phi(\hat{\beta}^{(\lambda)}, \lambda)}_{\in \mathbb{R}^{r \times p}} \underbrace{\left( \nabla_\beta^2 \Phi(\hat{\beta}^{(\lambda)}, \lambda) \right)^{-1}}_{\in \mathbb{R}^{p \times p}} \underbrace{\nabla \mathcal{C}(\hat{\beta}^{(\lambda)})}_{\in \mathbb{R}^p} . \quad (6)$$

**Proof** For a smooth convex function  $\beta \mapsto \Phi(\beta, \lambda)$  the first-order condition writes:

$$\nabla_\beta \Phi(\hat{\beta}^{(\lambda)}, \lambda) = 0 , \quad (7)$$

for any  $\hat{\beta}^{(\lambda)}$  solution of the inner problem. Moreover, if  $\lambda \mapsto \nabla_\beta \Phi(\hat{\beta}^{(\lambda)}, \lambda)$  is differentiable, differentiating [Equation \(7\)](#) with respect to  $\lambda$  leads to

$$\nabla_{\beta, \lambda}^2 \Phi(\hat{\beta}^{(\lambda)}, \lambda) + \hat{\mathcal{J}}_{(\lambda)}^\top \nabla_\beta^2 \Phi(\hat{\beta}^{(\lambda)}, \lambda) = 0 . \quad (8)$$

The Jacobian  $\hat{\mathcal{J}}_{(\lambda)}^\top$  is computed by solving the following linear system

$$\hat{\mathcal{J}}_{(\lambda)}^\top = - \underbrace{\nabla_{\beta, \lambda}^2 \Phi(\hat{\beta}^{(\lambda)}, \lambda)}_{\in \mathbb{R}^{r \times p}} \underbrace{\left( \nabla_\beta^2 \Phi(\hat{\beta}^{(\lambda)}, \lambda) \right)^{-1}}_{\in \mathbb{R}^{p \times p}} . \quad (9)$$

Plugging [Equation \(9\)](#) into [Equation \(3\)](#) yields the desired result. ■

The computation of the gradient via implicit differentiation ([Equation \(6\)](#)) involves the resolution of a  $p \times p$  linear system ([Bengio, 2000](#), Sec. 4). This potentially large linear system can be solved using different algorithms such as conjugate gradient ([Hestenes and Stiefel 1952](#), as in [Pedregosa 2016](#)) or fixed point methods ([Lions and Mercier 1979](#); [Tseng and Yun 2009](#), as in [Grazzi et al. 2020](#)). Implicit differentiation has been used for model selection of multiple estimators with smooth regularization term: kernel-based models ([Chapelle et al., 2002](#); [Seeger, 2008](#)), weighted Ridge estimator ([Foo et al., 2008](#)), neural networks ([Lorraine et al., 2019](#)) or meta-learning ([Rajeswaran et al., 2019](#)). In addition to hyperparameter selection, it has been applied successfully in natural language processing ([Bai et al., 2019](#)) and computer vision ([Bai et al., 2020](#)).

[Problem \(1\)](#) is typically solved using iterative solvers. In practice, the number of iterations is limited to reduce computation time, and also since very precise solutions are

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3. Note that *implicit* refers to the implicit function theorem, but leads to an *explicit* formula for the gradient.



generally not necessary for machine learning tasks. Thus, Equation (7) is not exactly satisfied at machine precision, and consequently the linear system to solve Equation (6) does not lead to the exact gradient  $\nabla_\lambda \mathcal{L}(\lambda)$ , see Ablin et al. (2020) for quantitative convergence results. However, Pedregosa (2016) showed that one can resort to *approximate gradients* when the inner problem is smooth, justifying that implicit differentiation can be applied using an approximation of  $\hat{\beta}$ . Interestingly, this approximation scheme was shown to yield significant practical speedups when solving Problem (2), while preserving theoretical properties of convergence toward the optimum. Practitioners now have access to powerful software to use implicit differentiation with smooth inner optimization problems (Blondel et al., 2021).

*Iterative differentiation.* Iterative differentiation computes the gradient  $\nabla_\lambda \mathcal{L}(\lambda)$  by differentiating through the iterates of the algorithm used to solve Problem (1). Iterative differentiation can be applied using the forward-mode (Wengert 1964) or the reverse-mode (Linnainmaa 1970). Both rely on the chain rule, the gradient being decomposed as a large product of matrices, computed either in a forward or backward way. Note that forward and reverse modes are algorithm-dependent: in this section we illustrate iterative differentiation for proximal gradient descent (PGD, Lions and Mercier 1979; Combettes and Wajs 2005), using the forward-mode (Algorithm 1), and the reverse-mode (Algorithm 2).

The most popular method in automatic differentiation is the reverse-mode, a cornerstone of deep learning (Goodfellow et al., 2016, Chap. 8). Iterative differentiation for hyperparameter optimization can be traced back to Domke (2012), who derived (for smooth loss functions) a reverse-mode with gradient descent, heavy ball and L-BFGS algorithms. It first computes the solution of the optimization Problem (1) using an iterative solver, but requires storing the iterates along the computation for a backward evaluation of the hypergradient (Algorithm 2). Maclaurin et al. (2015) used the reverse-mode on stochastic gradient descent to select thousands of hyperparameters. Alternatively, the forward-mode computes jointly the solution along with the gradient  $\nabla_\lambda \mathcal{L}(\lambda)$ . The forward-mode has been applied to hyperparameter optimization with smooth inner problems by Franceschi et al. (2017). Deledalle et al. (2014) paved the way for applying it to non-smooth optimization problems. The forward-mode is memory efficient (no iterates storage) but more computationally expensive when the number of hyperparameters ( $r$ ) is large; see Baydin et al. (2018) for a survey.

*Resolution of the bilevel Problem (2).* From a theoretical point of view, solving Problem (2) using gradient-based methods is also challenging, and results in the literature are quite scarce. Kunisch and Pock (2013) studied the convergence of a semi-Newton algorithm where both the outer and inner problems are smooth. Franceschi et al. (2018) gave similar results with weaker assumptions to unify hyperparameter optimization and meta-learning with a bilevel point of view. They required the inner problem to have a unique solution for all  $\lambda > 0$  but do not have second-order assumptions on  $\Phi$ . Recent results (Ghadimi and Wang, 2018; Ji et al., 2020) have provided quantitative convergence toward a global solution of Problem (2), under the assumption that the inner problem is strongly convex and one has the exact knowledge of the hypergradient Lipschitz constant.

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**Algorithm 1** FORWARD-MODE PGD
 

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**input** :  $\lambda \in \mathbb{R}^r, \gamma > 0, n_{\text{iter}} \in \mathbb{N}, \beta^{(0)} \in \mathbb{R}^p,$   
 $\mathcal{J}^{(0)} \in \mathbb{R}^{p \times r}$   
 // jointly compute coef. & Jacobian  
**for**  $k = 1, \dots, n_{\text{iter}}$  **do**  
     // update the regression coefficients  
      $z^{(k)} = \beta^{(k-1)} - \gamma \nabla f(\beta^{(k-1)})$  // GD step  
      $\text{d}z^{(k)} = \mathcal{J}^{(k-1)} - \gamma \nabla^2 f(\beta^{(k-1)}) \mathcal{J}^{(k-1)}$   
      $\beta^{(k)} = \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)})$  // prox. step  
     // update the Jacobian  
      $\mathcal{J}^{(k)} = \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)}) \odot \text{d}z^{(k)}$   
      $\mathcal{J}^{(k)} += \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)})$  //  $\mathcal{O}(pr)$   
 $v = \nabla \mathcal{C}(\beta^{n_{\text{iter}}})$   
**return**  $\beta^{n_{\text{iter}}}, \mathcal{J}^{n_{\text{iter}^\top} v}$

---



---

**Algorithm 2** REVERSE-MODE PGD
 

---

**input** :  $\lambda \in \mathbb{R}^r, \gamma > 0, n_{\text{iter}} \in \mathbb{N}, \beta^{(0)} \in \mathbb{R}^p$   
 // computation of  $\hat{\beta}$   
**for**  $k = 1, \dots, n_{\text{iter}}$  **do**  
      $z^{(k)} = \beta^{(k-1)} - \gamma \nabla f(\beta^{(k-1)})$  // GD step  
      $\beta^{(k)} = \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)})$  // prox. step  
 // backward computation of the gradient  $g$   
 $v = \nabla \mathcal{C}(\beta^{n_{\text{iter}}}), h = 0_{\mathbb{R}^r}$   
**for**  $k = n_{\text{iter}}, n_{\text{iter}} - 1, \dots, 1$  **do**  
      $h += v^\top \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)})$  //  $\mathcal{O}(pr)$   
      $v \leftarrow \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)}) \odot v$  //  $\mathcal{O}(p)$   
      $v \leftarrow (\text{Id} - \gamma \nabla^2 f(\beta^{(k)}))v$  //  $\mathcal{O}(np)$   
**return**  $\beta^{n_{\text{iter}}}, h$

---

### 3. Bilevel Optimization with Non-Smooth Inner Problems

We recalled above how to compute hypergradients when the inner optimization problem is smooth. In this section we tackle the bilevel optimization [Problem \(2\)](#) with non-smooth inner optimization [Problem \(1\)](#). Handling non-smooth inner problems requires specific tools detailed in [Section 3.1](#). We then show how to compute gradients with non-smooth inner problems using implicit differentiation ([Section 3.2](#)) or iterative differentiation ([Section 3.3](#)). In [Section 3.4](#) we tackle the problem of approximate gradient for a non-smooth inner optimization problem. Finally, we propose in [Section 3.6](#) an algorithm to solve the bilevel optimization [Problem \(2\)](#).

#### 3.1 Theoretical Framework

*Differentiability of the regularization path.* Before applying first-order methods to tackle [Problem \(2\)](#), one must ensure that the regularization path  $\lambda \mapsto \hat{\beta}^{(\lambda)}$  is almost everywhere differentiable (as in [Figure 2](#)). This is the case for the Lasso ([Mairal and Yu, 2012](#)) and the SVM ([Pontil and Verri, 1998](#)) since solution paths are piecewise differentiable (see [Figure 2](#)). Results for nonquadratic datafitting terms are scarcer: [Friedman et al. \(2010\)](#) address the practical resolution of sparse logistic regression, but stay evasive regarding the differentiability of the regularization path. In the general case for problems of the form [Problem \(1\)](#), we believe it is an open question and leave it for future work. *Differentiability of proximal operators.* The key point to obtain an implicit differentiation formula for non-smooth inner problems is to differentiate the fixed point equation of proximal gradient descent. From a theoretical point of view, ensuring this differentiability at the optimum is non-trivial: [Poliquin and Rockafellar \(1996, Thm. 3.8\)](#) showed that under a *twice epi-differentiability*

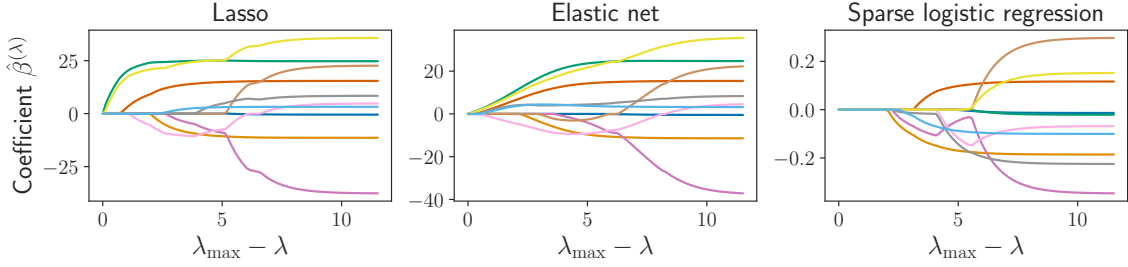


Figure 2: *Regularization paths* (coefficient values as a function of  $\lambda$ ), on the *diabetes* and *breast cancer* data sets for the Lasso, the elastic net and sparse logistic regression. This illustrates the weak differentiability of the paths. We used *diabetes* for the Lasso and the elastic net, and the 10 first features of *breast cancer* for the sparse logistic regression.

condition the proximal operator is differentiable at optimum. For the convergence of forward and reverse modes in the non-smooth case, one has to ensure that, after enough iterations, the updates of the algorithms become differentiable. [Deledalle et al. \(2014\)](#) justified (weak) differentiability of proximal operators as they are non-expansive. However this may not be a sufficient condition, see [Bolte and Pauwels \(2020a,b\)](#). In our case, we show differentiability after *support identification* of the algorithms: active constraints are identified after a finite number of iterations by proximal gradient descent ([Liang et al., 2014](#); [Vaiter et al., 2018](#)) and proximal coordinate descent, see [Nutini \(2018, Sec. 6.2\)](#) or [Klopfenstein et al. \(2020\)](#). Once these constraints have been identified convergence is linear towards the Jacobian (see [Theorem 12](#) and [Figures 3, 10](#) and [11](#)).

For the rest of this paper, we consider the bilevel optimization [Problem \(2\)](#) with the following assumptions on the inner [Problem \(1\)](#).

**Assumption 2** Smoothness. *The function  $f : \mathbb{R}^p \rightarrow \mathbb{R}$  is a convex, differentiable function, with a  $L$ -Lipschitz gradient.*

**Assumption 3** Proper, closed, convex. *For all  $\lambda \in \mathbb{R}^r$ , for any  $j \in [p]$ , the function  $g_j(\cdot, \lambda) : \mathbb{R} \rightarrow \mathbb{R}$  is proper, closed and convex.*

**Assumption 4** Non-degeneracy *The problem admits at least one solution*

$$\arg \min_{\beta \in \mathbb{R}^p} \Phi(\beta, \lambda) \neq \emptyset ,$$

and, for any  $\hat{\beta}$  solution of [Problem \(1\)](#), we have

$$-\nabla f(\hat{\beta}) \in \text{ri} \left( \partial_{\beta} g(\hat{\beta}, \lambda) \right) .$$

To be able to extend iterative and implicit differentiation to the non-smooth case, we need to introduce the notion of generalized support.

**Definition 5** Generalized support, (Nutini et al., 2019, Def. 1). For a solution  $\hat{\beta} \in \arg \min_{\beta \in \mathbb{R}^p} \Phi(\beta, \lambda)$ , its generalized support  $\hat{S} \subseteq [p]$  is the set of indices  $j \in [p]$  such that  $g_j$  is differentiable at  $\hat{\beta}_j$

$$\hat{S} \triangleq \{j \in [p] : \partial_{\beta} g_j(\hat{\beta}_j, \lambda) \text{ is a singleton}\} .$$

An iterative algorithm is said to achieve finite support identification if its iterates  $\beta^{(k)}$  converge to  $\hat{\beta}$ , and there exists  $K \geq 0$  such that for all  $j \notin \hat{S}$ , for all  $k \geq K$ ,  $\beta_j^{(k)} = \hat{\beta}_j$ .

*Examples.* For the  $\ell_1$  norm (promoting sparsity),  $g_j(\hat{\beta}_j, \lambda) = e^\lambda |\hat{\beta}_j|$ , the generalized support is  $\hat{S} \triangleq \{j \in [p] : \hat{\beta}_j \neq 0\}$ . This set corresponds to the indices of the non-zero coefficients, which is the usual support definition. For the SVM estimator,  $g_j(\hat{\beta}_j, \lambda) = \iota_{[0, e^\lambda]}(\hat{\beta}_j)$ . This function is non-differentiable at 0 and at  $e^\lambda$ . The generalized support for the SVM estimator then corresponds to the set of indices such that  $\hat{\beta}_j \in ]0, e^\lambda[$ .

Finally, to prove local linear convergence of the Jacobian we assume regularity and strong convexity on the generalized support.

**Assumption 6** Locally  $\mathcal{C}^2$  and  $\mathcal{C}^3$ . The map  $\beta \mapsto f(\beta)$  is locally  $\mathcal{C}^3$  around  $\hat{\beta}$ . For all  $\lambda \in \mathbb{R}^r$ , for all  $j \in \hat{S}$  the map  $g_j(\cdot, \lambda)$  is locally  $\mathcal{C}^2$  around  $\hat{\beta}_j$ .

**Assumption 7** Restricted injectivity. Let  $\hat{\beta}$  be a solution of Problem (1) and  $\hat{S}$  its generalized support. The solution  $\hat{\beta}$  satisfies the following restricted injectivity condition

$$\nabla_{\hat{S}, \hat{S}}^2 f(\hat{\beta}) \succ 0 .$$

Assumptions 2 and 3 are classical to ensure inner problems can be solved using proximal algorithms. Assumption 4 can be seen as a generalization of constraint qualifications (Hare and Lewis, 2007, Sec. 1) and is crucial to ensure support identification. Note that Assumption 4 is hard to verify in advance in practice, and hard to relax theoretically (Fadili et al., 2018). Assumptions 6 and 7 are classical for the analysis (Liang et al., 2017) and sufficient to derive rates of convergence for the Jacobian of the inner problem once the generalized support has been identified. Assumption 6 is met for usual quadratic and logistic losses, as well as for usual penalties ( $\ell_1$ ,  $\ell_1 + \ell_2$ -squared, box constraints). For instance for the Lasso Assumption 7 boils down to  $X_S^\top X_S \succ 0$ , which holds with probability one if the entries of  $X$  are drawn from a continuous distribution (Tibshirani, 2013).

The next lemma guarantees uniqueness of Problem (1) under Assumptions 4 and 7.

**Lemma 8** (Liang et al., 2017, Prop. 4.1). Assume that there exists a neighborhood  $\Lambda$  of  $\lambda$  such that Assumptions 4 and 7 are satisfied for every  $\lambda \in \Lambda$ . Then for every  $\lambda \in \Lambda$ , Problem (1) has a unique solution, and the map  $\lambda \mapsto \hat{\beta}^{(\lambda)}$  is well-defined on  $\Lambda$ .

We first show how implicit and iterative differentiation can be used with a non-smooth inner problem. [Peyré and Fadili \(2011\)](#) proposed to smooth the inner optimization problem, [Ochs et al. \(2015\)](#); [Frecon et al. \(2018\)](#) relied on the forward-mode combined with Bregman iterations to get differentiable steps. For non-smooth optimization problems, implicit differentiation has been considered for (constrained) convex optimization problems ([Gould et al., 2016](#); [Amos and Kolter, 2017](#); [Agrawal et al., 2019](#)), Lasso-type problems ([Mairal et al., 2012](#); [Bertrand et al., 2020](#)), total variation penalties ([Cherkaoui et al., 2020](#)) and generalized to strongly monotone operators ([Winston and Kolter, 2020](#)).

### 3.2 Hypergradient Computation: Implicit Differentiation

The exact proof of [Theorem 1](#) cannot be applied when  $\beta \mapsto \Phi(\beta, \lambda)$  is non-smooth, as [Equations \(7\) and \(8\)](#) no longer hold. Nevertheless, instead of the optimality condition of smooth optimization, [Equation \(7\)](#), one can leverage the fixed point iteration of proximal gradient descent, which we will see in [Equation \(12\)](#). The main theoretical challenge is to show the differentiability of the function  $\beta \mapsto \text{prox}_{\gamma g}(\beta - \gamma \nabla f(\beta))$ . Besides, taking advantage of the generalized sparsity of the regression coefficients  $\hat{\beta}^{(\lambda)}$ , one can show that the Jacobian  $\hat{\mathcal{J}}$  is row-sparse, leading to substantial computational benefits when computing the hypergradient  $\nabla_{\lambda} \mathcal{L}(\lambda)$  for [Problem \(1\)](#),

**Theorem 9** Non-smooth implicit formula *Suppose [Assumptions 2, 3 and 6](#) hold. Let  $0 < \gamma \leq 1/L$ , where  $L$  is the Lipschitz constant of  $\nabla f$ . Let  $\lambda \in \mathbb{R}^r$ ,  $\Lambda$  be a neighborhood of  $\lambda$ , and  $\Gamma^{\Lambda} \triangleq \left\{ \hat{\beta}^{(\lambda)} - \gamma \nabla f(\hat{\beta}^{(\lambda)}) : \lambda \in \Lambda \right\}$ . In addition,*

(H1) *Suppose [Assumptions 4 and 7](#) hold on  $\Lambda$ .*

(H2) *Suppose  $\lambda \mapsto \hat{\beta}^{(\lambda)}$  is continuously differentiable on  $\Lambda$ .*

(H3) *Suppose for all  $z \in \Gamma^{\Lambda}$ ,  $\lambda \mapsto \text{prox}_{\gamma g(\cdot, \lambda)}(z)$  is continuously differentiable on  $\Lambda$ .*

(H4) *Suppose  $\partial_z \text{prox}_{\gamma g(\cdot, \lambda)}$  and  $\partial_{\lambda} \text{prox}_{\gamma g(\cdot, \lambda)}$  are Lipschitz continuous on  $\Gamma^{\Lambda} \times \Lambda$ .*

Let  $\hat{\beta} \triangleq \hat{\beta}^{(\lambda)}$  be the solution of [Problem \(1\)](#),  $\hat{S}$  its generalized support of cardinality  $\hat{s}$ . Then the Jacobian  $\hat{\mathcal{J}}$  of the inner [Problem \(1\)](#) is given by the following formula,

$$\hat{z} = \hat{\beta} - \gamma \nabla f(\hat{\beta}), \text{ and } A \triangleq \text{Id}_{\hat{s}} - \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}} \odot \left( \text{Id}_{\hat{s}} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\hat{\beta}) \right)$$

$$\hat{\mathcal{J}}_{\hat{S}^c} = \partial_{\lambda} \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}^c} , \quad (10)$$

$$\hat{\mathcal{J}}_{\hat{S}} = A^{-1} \left( \partial_{\lambda} \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}} - \gamma \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}} \odot \nabla_{\hat{S}, \hat{S}^c}^2 f(\hat{\beta}) \hat{\mathcal{J}}_{\hat{S}^c} \right) . \quad (11)$$

**Proof** According to [Theorem 8](#), [Assumptions 4 and 7](#) ensure [Problem \(1\)](#) has a unique minimizer and  $\lambda \mapsto \hat{\beta}^{(\lambda)}$  is well-defined on  $\Lambda$ . We consider the proximal gradient descent fixed point equation:

$$\hat{\beta}^{(\lambda)} = \text{prox}_{\gamma g(\cdot, \lambda)} \left( \hat{\beta}^{(\lambda)} - \gamma \nabla f(\hat{\beta}^{(\lambda)}) \right) . \quad (12)$$

Together with the conclusion of [Theorem 8](#), [Assumptions 2](#) and [6](#), and given [\(H2\)](#), [\(H3\)](#) and [\(H4\)](#), we have that  $\lambda \mapsto \psi\left(\beta^{(\lambda)} - \gamma \nabla f(\hat{\beta}^{(\lambda)}), \lambda\right) \triangleq \text{prox}_{\gamma g(\cdot, \lambda)}\left(\hat{\beta}^{(\lambda)} - \gamma \nabla f(\hat{\beta}^{(\lambda)})\right)$  is differentiable at  $\lambda$ . One can thus differentiate [Equation \(12\)](#) with respect to  $\lambda$ , which leads to

$$\hat{\mathcal{J}} = \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z}) \odot \left(\text{Id} - \gamma \nabla^2 f(\hat{\beta})\right) \hat{\mathcal{J}} + \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z}) \quad , \quad (13)$$

with  $\hat{z} = \hat{\beta} - \gamma \nabla f(\hat{\beta})$ . In addition to  $0 < \gamma < 1/L \leq 1/L_j$ , the separability of  $g$  and [Assumptions 2](#) to [4](#) and [6](#) ensure (see [Theorem 20](#)) that for any  $j \in \hat{S}^c$ ,

$$\partial_z \text{prox}_{\gamma g_j(\cdot, \lambda)}\left(\hat{\beta}_j - \gamma \nabla_j f(\hat{\beta})\right) = 0 \quad . \quad (14)$$

Plugging [Equation \(14\)](#) into [Equation \(13\)](#) ensures [Equation \(10\)](#) for all  $j \in \hat{S}^c$

$$\hat{\mathcal{J}}_j = \partial_\lambda \text{prox}_{\gamma g_j(\cdot, \lambda)}\left(\hat{\beta}_j - \gamma \nabla_j f(\hat{\beta})\right) \quad . \quad (15)$$

Plugging [Equations \(14\)](#) and [\(15\)](#) into [Equation \(13\)](#) shows that the Jacobian restricted on the generalized support  $\hat{S}$  satisfies the following linear system

$$\begin{aligned} \left(\text{Id}_{\hat{S}} - \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}} \odot (\text{Id}_{\hat{S}} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\hat{\beta}))\right) \hat{\mathcal{J}}_{\hat{S}} = \\ -\gamma \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}} \odot \nabla_{\hat{S}, \hat{S}^c}^2 f(\hat{\beta}) \hat{\mathcal{J}}_{\hat{S}^c} + \partial_\lambda \text{prox}_g(\hat{z})_{\hat{S}} \quad . \end{aligned}$$

Since  $0 < \gamma \leq 1/L$ ,

$$\begin{aligned} \|\partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}} \odot (\text{Id}_{\hat{S}} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\hat{\beta}))\|_2 &\leq \|\partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}}\| \cdot \|\text{Id}_{\hat{S}} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\hat{\beta})\|_2 \\ &< 1 \quad . \end{aligned} \quad (16)$$

Since [Equation \(16\)](#) holds,  $A \triangleq \text{Id}_{\hat{S}} - \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}} \odot (\text{Id}_{\hat{S}} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\hat{\beta}))$  is invertible, which leads to [Equation \(11\)](#). ■

**Remark 10** *In the smooth case a  $p \times p$  linear system is needed to compute the Jacobian in [Equation \(9\)](#). For non-smooth problems this is reduced to an  $\hat{s} \times \hat{s}$  linear system ( $\hat{s} \leq p$  being the size of the generalized support, e.g., the number of non-zero coefficients for the Lasso). This leads to significant speedups in practice, especially for very sparse vector  $\hat{\beta}^{(\lambda)}$ .*

**Remark 11** *To obtain [Theorem 9](#) we differentiated the fixed point equation of proximal gradient descent, though one could differentiate other fixed point equations (such as the one from proximal coordinate descent). The value of the Jacobian  $\hat{\mathcal{J}}$  obtained with different fixed point equations would be the same, yet the associated systems could have different numerical stability properties. We leave this analysis to future work.*

### 3.3 Hypergradient Computation: Iterative Differentiation

Instead of implicit differentiation, it is also possible to use iterative differentiation on proximal solvers. In section [Section 2](#) we presented forward and reverse modes differentiation of proximal gradient descent ([Algorithms 1](#) and [2](#)). In this section we study the iterative differentiation of proximal coordinate descent ([Algorithms 3](#) and [4](#)). To instantiate algorithms easily on problems such as the Lasso, partial derivatives of usual proximal operators can be found in [Table 3](#).

For coordinate descent, the computation of the iterative Jacobian in a forward way involves differentiating the following update

$$\begin{aligned} z_j &\leftarrow \beta_j - \gamma_j \nabla_j f(\beta) \\ \beta_j &\leftarrow \text{prox}_{\gamma_j g_j}(\beta_j - \gamma_j \nabla_j f(\beta)) \\ \mathcal{J}_j &\leftarrow \underbrace{\partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j)}_{\in \mathbb{R}} \underbrace{(\mathcal{J}_j - \gamma_j \nabla_{j:}^2 f(\beta) \mathcal{J})}_{\in \mathbb{R}^p} + \underbrace{\partial_\lambda \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j)}_{\in \mathbb{R}^p} . \end{aligned}$$

We address now the convergence of the iterative Jacobian scheme, a question which remained open in [Deledalle et al. \(2014, Section 4.1\)](#). We show next that the forward-mode converges to the Jacobian in the non-smooth separable setting of this paper. Moreover, we prove that the iterative Jacobian convergence is locally linear after support identification.

**Theorem 12** Local linear convergence of the Jacobian. *Let  $0 < \gamma \leq 1/L$ . Suppose [Assumptions 2](#), [3](#) and [6](#) hold. Let  $\lambda \in \mathbb{R}^r$ ,  $\Lambda$  be a neighborhood of  $\lambda$ , and  $\Gamma^\Lambda \triangleq \{\hat{\beta}^{(\lambda)} - \gamma \nabla f(\hat{\beta}^{(\lambda)}) : \lambda \in \Lambda\}$ . In addition, suppose hypotheses [\(H1\)](#) to [\(H4\)](#) from [Theorem 9](#) are satisfied and the sequence  $(\beta^{(k)})_{k \in \mathbb{N}}$  generated by [Algorithm 1](#) (respectively by [Algorithm 3](#)) converges toward  $\hat{\beta}$ .*

*Then, the sequence of Jacobians  $(\mathcal{J}^{(k)})_{k \geq 0}$  generated by the forward-mode differentiation of proximal gradient descent ([Algorithm 1](#)) (respectively by forward-mode differentiation of proximal coordinate descent, [Algorithm 3](#)) converges locally linearly towards  $\hat{\mathcal{J}}$ .*

Proof of [Theorem 12](#) can be found in [Appendix C](#).

*Comments on [Figure 3](#).* We illustrate the results of [Theorem 12](#) on SVM (for the Lasso and sparse logistic regression, see [Figures 10](#) and [11](#) in [Appendix D](#)) for multiple data sets (*leukemia*, *rcv1*, *news20* and *real-sim*<sup>4</sup>). The values of the hyperparameters  $\lambda$  are summarized in [Table 6](#). Regression coefficients  $\hat{\beta}^{(\lambda)}$  were computed to machine precision (up to duality gap smaller than  $10^{-16}$ ) using a state-of-the-art coordinate descent solver implemented in **Lightning** ([Blondel and Pedregosa, 2016](#)). The exact Jacobian was computed via implicit differentiation ([Equation \(11\)](#)). Once these quantities were obtained, we used the forward-mode differentiation of proximal coordinate descent ([Algorithm 3](#)) and monitored the distance between the iterates of the regression coefficients  $\beta^{(k)}$  and the exact solution

4. Data available on the *libsvm* website: <https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/>



**Algorithm 3** FORWARD-MODE PCD

---

**input** :  $X \in \mathbb{R}^{n \times p}, y \in \mathbb{R}^n, \lambda \in \mathbb{R}^r, n_{\text{iter}} \in \mathbb{N}, \beta \in \mathbb{R}^p, \mathcal{J} \in \mathbb{R}^{p \times r}, \gamma_1, \dots, \gamma_p$   
 // jointly compute coef. & Jacobian  
**for**  $k = 1, \dots, n_{\text{iter}}$  **do**  
     **for**  $j = 1, \dots, p$  **do**  
         // update the regression coefficients  
          $z_j \leftarrow \beta_j - \gamma_j \nabla_j f(\beta)$  // CD step  
          $dz_j \leftarrow \mathcal{J}_j: - \gamma_j \nabla_{j:}^2 f(\beta) \mathcal{J}$   
          $\beta_j \leftarrow \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j)$  // prox. step  
         // update the Jacobian  
         // diff. with respect to  $\lambda$   
          $\mathcal{J}_j: \leftarrow \partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j) dz_j$   
          $\mathcal{J}_j: += \partial_\lambda \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j)$   
      $\beta^{(k)} = \beta$   
      $\mathcal{J}^{(k)} = \mathcal{J}$   
**return**  $\beta^{n_{\text{iter}}}, \mathcal{J}^\top v$

---

**Algorithm 4** REVERSE-MODE PCD

---

**input** :  $X \in \mathbb{R}^{n \times p}, y \in \mathbb{R}^n, \lambda \in \mathbb{R}^r, n_{\text{iter}} \in \mathbb{N}, \beta \in \mathbb{R}^p, \gamma_1, \dots, \gamma_p$   
 // compute coef.  
**for**  $k = 1, \dots, n_{\text{iter}}$  **do**  
     **for**  $j = 1, \dots, p$  **do**  
         // update the regression coefficients  
          $z_j \leftarrow \beta_j - \gamma_j \nabla_j f(\beta)$  // CD step  
          $\beta_j \leftarrow \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j)$  // prox. step  
          $\beta^{(k, j)} = \beta; z_j^{(k)} = z_j$  // store iterates  
     // compute gradient  $g$  in a backward way  
      $v = \nabla C(\beta^{n_{\text{iter}}}), h = 0_{\mathbb{R}^r}$   
     **for**  $k = n_{\text{iter}}, n_{\text{iter}} - 1, \dots, 1$  **do**  
         **for**  $j = p, \dots, 1$  **do**  
              $h -= \gamma_j v_j \partial_\lambda \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j^{(k)})$   
              $v_j *= \partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j^{(k)})$   
              $v -= \gamma_j v_j \nabla_{j:}^2 f(\beta^{(k, j)})$  //  $\mathcal{O}(np)$   
**return**  $\beta^{n_{\text{iter}}}, h$

---

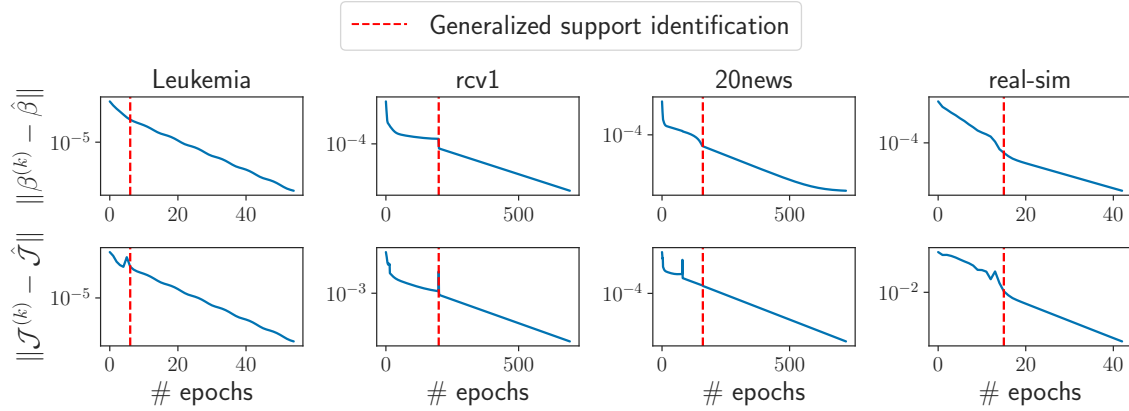


Figure 3: *Local linear convergence of the Jacobian for the SVM.* Distance to optimum for the coefficients  $\beta$  (top) and the Jacobian  $\mathcal{J}$  (bottom) of the forward-mode differentiation of proximal coordinate descent (Algorithm 3) on multiple data sets. One epoch corresponds to one pass over the data, *i.e.*, one iteration with proximal gradient descent.

$\hat{\beta}$ . We also monitored the distance between the iterates of the Jacobian  $\mathcal{J}^{(k)}$  and the exact Jacobian  $\hat{\mathcal{J}}$ . The red vertical dashed line represents the iteration number where support

identification happens. Once the support is identified, [Figures 3, 10 and 11](#) illustrate the linear convergence of the Jacobian. However, the behavior of the iterative Jacobian before support identification is more erratic and not even monotone.

### 3.4 Hypergradient Computation with Approximate Gradients

As mentioned in [Section 2](#), relying on iterative algorithms to solve [Problem \(1\)](#), one only has access to an approximation of  $\hat{\beta}^{(\lambda)}$ : this may lead to numerical errors when computing the gradient in [Theorem 9](#). Extending the result of [Pedregosa \(2016, Thm. 1\)](#), which states that hypergradients can be computed approximately, we give a stability result for the computation of approximate hypergradients in the case of non-smooth inner problems. For this purpose we need to add several assumptions to the previous framework.

**Theorem 13** Bound on the error of approximate hypergradient. *For  $\lambda \in \mathbb{R}^r$ , let  $\hat{\beta}^{(\lambda)} \in \mathbb{R}^p$  be the exact solution of the inner [Problem \(1\)](#), and  $\hat{S}$  its generalized support. Suppose [Assumptions 2, 3 and 6](#) hold. Let  $\Lambda$  be a neighborhood of  $\lambda$ , and  $\Gamma^\Lambda \triangleq \left\{ \hat{\beta}^{(\lambda)} - \gamma \nabla f(\hat{\beta}^{(\lambda)}) : \lambda \in \Lambda \right\}$ . Suppose hypotheses [\(H1\)](#) to [\(H4\)](#) from [Theorem 9](#) are satisfied. In addition suppose*

*(H5) The application  $\beta \mapsto \nabla^2 f(\beta)$  is Lipschitz continuous.*

*(H6) The criterion  $\beta \mapsto \nabla \mathcal{C}(\beta)$  is Lipschitz continuous.*

*(H7) Both optimization problems in [Algorithm 5](#) are solved up to precision  $\epsilon$  with support identification:  $\|\beta^{(\lambda)} - \hat{\beta}^{(\lambda)}\| \leq \epsilon$ ,  $A^\top$  is invertible, and  $\|A^{-1\top} \nabla_{\hat{S}} \mathcal{C}(\beta^{(\lambda)}) - v\| \leq \epsilon$ .*

*Then the error on the approximate hypergradient  $h$  returned by [Algorithm 5](#) is of the order of magnitude of the error  $\epsilon$  on  $\beta^{(\lambda)}$  and  $v$*

$$\|\nabla \mathcal{L}(\lambda) - h\| = \mathcal{O}(\epsilon) .$$

Proof of [Theorem 13](#) can be found in [Appendix C.1](#). Following the analysis of [Pedregosa \(2016\)](#), two sources of approximation errors arise when computing the hypergradient: one from the inexact computation of  $\hat{\beta}$ , and another from the approximate resolution of the linear system. [Theorem 13](#) states that if the inner optimization problem and the linear system are solved up to precision  $\epsilon$ , i.e.,  $\|\hat{\beta}^{(\lambda)} - \beta^{(\lambda)}\| \leq \epsilon$  and  $\|A^{-1\top} \nabla_{\hat{S}} \mathcal{C}(\beta^{(\lambda)}) - v\| \leq \epsilon$ , then the approximation on the hypergradient is also of the order of  $\epsilon$ .

**Remark 14** *The Lipschitz continuity of the proximity operator with respect to  $\lambda$  [\(H4\)](#) is satisfied for usual proximal operators, in particular all the operators in [Table 3](#). The Lipschitz continuity of the Hessian and the criterion, hypotheses [\(H5\)](#) and [\(H6\)](#), are satisfied for usual machine learning loss functions and criteria, such as the least squares and the logistic loss.*

**Remark 15** *To simplify the analysis, we used the same tolerance for the resolution of the inner [Problem \(1\)](#) and the resolution of the linear system. [Theorem 13](#) gives intuition on the fact that the inner problem does not need to be solved at high precision to lead to good hypergradients estimation. Note that in practice one does not easily control the distance between the approximate solution and the exact one  $\|\beta^{(k)} - \hat{\beta}\|$ : most softwares provide a solution up to a given duality gap (sometimes even other criteria), not  $\|\beta^{(k)} - \hat{\beta}\|$ .*

### 3.5 Proposed Method for Hypergradient Computation

We now describe our proposed method to compute the hypergradient of [Problem \(2\)](#). In order to take advantage of the sparsity induced by the generalized support, we propose an implicit differentiation algorithm for non-smooth inner problem that can be found in [Algorithm 5](#). First, we compute a solution of the inner [Problem \(1\)](#) using a solver identifying the generalized support ([Liang et al., 2014](#); [Klopfenstein et al., 2020](#)). Then, the hypergradient is computed by solving the linear system in [Equation \(11\)](#). This linear system, as mentioned in [Section 2](#), can be solved using multiple algorithms, including conjugate gradient or fixed point methods. [Table 4](#) summarizes the computational complexity in space and time of the described algorithms.

Table 4: Cost in time and space for each method:  $p$  is the number of features,  $n$  the number of samples,  $r$  the number of hyperparameters, and  $\hat{s}$  is the size of the generalized support ([Theorem 5](#),  $\hat{s} \leq p$  and usually  $\hat{s} \ll p$ ). The number of iterations of the inner solver is noted  $n_{\text{iter}}$ , the number of iterations of the solver of the linear system is noted  $n_{\text{sys}}$ .

Differentiation	Algorithm	Space	Time
Forward-mode PGD	<a href="#">Algorithm 1</a>	$\mathcal{O}(pr)$	$\mathcal{O}(nprn_{\text{iter}})$
Reverse-mode PGD	<a href="#">Algorithm 2</a>	$\mathcal{O}(pn_{\text{iter}})$	$\mathcal{O}(nppn_{\text{iter}} + nppn_{\text{iter}})$
Forward-mode PCD	<a href="#">Algorithm 3</a>	$\mathcal{O}(pr)$	$\mathcal{O}(nprn_{\text{iter}})$
Reverse-mode PCD	<a href="#">Algorithm 4</a>	$\mathcal{O}(pn_{\text{iter}})$	$\mathcal{O}(nppn_{\text{iter}} + np^2n_{\text{iter}})$
Implicit differentiation	<a href="#">Algorithm 5</a>	$\mathcal{O}(p + \hat{s})$	$\mathcal{O}(nppn_{\text{iter}} + n\hat{s}n_{\text{sys}})$

### 3.6 Resolution of the Bilevel Optimization [Problem \(2\)](#)

From a practical point of view, once the hypergradient has been computed, first-order methods require the definition of a step size to solve the non-convex [Problem \(2\)](#). As the Lipschitz constant is not available for the outer problem, first-order methods need to rely on other strategies, such as:

- Gradient descent with manually adjusted fixed step sizes ([Frecon et al., 2018](#); [Ji et al., 2020](#)). The main disadvantage of this technique is that it requires a careful tuning

of the step size for each experiment. In addition to being potentially tedious, it does not lead to an automatic procedure.

- L-BFGS (as in [Deledalle et al. 2014](#)). L-BFGS is a quasi-Newton algorithm that exploits past iterates to approximate the Hessian and propose a better descent direction, which is combined with some line search ([Nocedal and Wright, 2006](#)). Yet, due to the approximate gradient computation, we observed that L-BFGS did not always converge.
- ADAM ([Kingma and Ba, 2014](#)). It turned out to be inappropriate to the present setting. ADAM was very sensitive to the initial step size and required a careful tuning for each experiment.
- Iteration specific step sizes obtained by line search ([Pedregosa, 2016](#)). While the approach from [Pedregosa \(2016\)](#) requires no tuning, we observed that it could diverge when close to the optimum. The normalized gradient strategy ([Watt et al., 2020](#), Sec. 3.9)<sup>5</sup> proposed in [Algorithm 6](#), used in all the experiments, turned out to be robust and efficient across problems and data sets.

**Remark 16** Uniqueness. *The solution of [Problem \(1\)](#) may be non-unique, leading to a multi-valued regularization path  $\lambda \mapsto \hat{\beta}^{(\lambda)}$  ([Liu et al., 2020](#)) and requiring tools such as optimistic gradient ([Dempe et al., 2015](#), Chap. 3.8). Though it is not possible to ensure uniqueness in practice, we did not face experimental issues due to potential non-uniqueness. For the Lasso, this experimental observation can be theoretically justified ([Tibshirani, 2013](#)): when the design matrix is sampled from a continuous distribution, the solution of the Lasso is almost surely unique.*

**Remark 17** Initialization and warm start. *One advantage of the non-smooth case with the  $\ell_1$  norm is that one can find a good initialization point: there exists a value  $\lambda_{\max}$  (see [Table 1](#)) such that the solution of [Problem \(1\)](#) vanishes for  $\lambda \geq \lambda_{\max}$ . Hence, a convenient and robust initialization value can be chosen as  $e^\lambda = e^{\lambda_{\max}}/100$ . This is in contrast with the smooth case, where finding a good initialization heuristic is hard: starting in flat zones can lead to poor performance for gradient-based methods ([Pedregosa, 2016](#)). [Algorithm 5](#) is called multiple times in [Algorithm 6](#): several inner optimization problems and linear systems which are "similar" are solved successively. That is why we use warm-start to solve these problems.*

**Remark 18** Role of the step size  $\gamma$  in [Algorithm 5](#). *In all the convex penalties we used ( $\ell_1$ -norm,  $\ell_1 + \ell_2$ -squared norm, indicator function) the step size  $\gamma$  simplifies and does not appear in the implicit differentiation formula. Instantiations of [Algorithm 5](#) for the Lasso, the elastic net, the weighted Lasso and the dual of the SVM can be found in [Appendix A](#).*

5. [https://jermwatt.github.io/machine\\_learning\\_refined/notes/3\\_First\\_order\\_methods/3\\_9\\_Normalized.html](https://jermwatt.github.io/machine_learning_refined/notes/3_First_order_methods/3_9_Normalized.html)

---

**Algorithm 5** IMPLICIT DIFFERENTIATION
 

---

```

input :  $\lambda \in \mathbb{R}, \epsilon > 0$ 
init   :  $\gamma > 0$ 
        // compute the solution of inner problem
        Find  $\beta$  such that:  $\Phi(\beta, \lambda) - \Phi(\hat{\beta}, \lambda) \leq \epsilon$ 
        // compute the gradient
        Compute the generalized support  $S$  of  $\beta$ ,
         $z = \beta - \gamma \nabla f(\beta)$ 
         $\mathcal{J}_{S^c} = \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(z)_{S^c}$ 
         $s = |S|$ 
         $A = \text{Id}_s - \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(z)_S \odot (\text{Id}_s - \gamma \nabla_{S, S^c}^2 f(\beta))$ 
        Find  $v \in \mathbb{R}^s$  s.t.  $\|A^{-1\top} \nabla_S \mathcal{C}(\beta) - v\| \leq \epsilon$ 
         $B = \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(z)_S$ 
            $- \gamma \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(z)_S \odot \nabla_{S, S^c}^2 f(\beta) \mathcal{J}_{S^c}$ 
         $\nabla \mathcal{L}(\lambda) = \mathcal{J}_{S^c}^\top \nabla_{S^c} \mathcal{C}(\beta) + v^\top B$ 
return  $\mathcal{L}(\lambda) \triangleq \mathcal{C}(\beta), \nabla \mathcal{L}(\lambda)$ 
    
```

---



---

**Algorithm 6** GRADIENT DESCENT WITH APPROXIMATE GRADIENT
 

---

```

input :  $\lambda \in \mathbb{R}^r, (\epsilon_i)$ 
init   : use_adaptive_step_size = True
for  $i = 1, \dots, \text{iter}$  do
     $\lambda^{\text{old}} \leftarrow \lambda$ 
    // compute the value and the gradient
     $\mathcal{L}(\lambda), \nabla \mathcal{L}(\lambda) \leftarrow \text{Algorithm 5}(X, y, \lambda, \epsilon_i)$ 
    if use_adaptive_step_size then
         $\alpha = 1 / \|\nabla \mathcal{L}(\lambda)\|$ 
     $\lambda \leftarrow \alpha \nabla \mathcal{L}(\lambda)$  // gradient step
    if  $\mathcal{L}(\lambda) > \mathcal{L}(\lambda^{\text{old}})$  then
        use_adaptive_step_size = False
         $\alpha /= 10$ 
return  $\lambda$ 
    
```

---

## 4. Experiments

In this section, we illustrate the benefits of our proposed [Algorithm 5](#) to compute hypergradients and [Algorithm 6](#) to solve [Problem \(2\)](#). Our package, `sparse-ho`, is implemented in Python. It relies on Numpy ([Harris et al., 2020](#)), Numba ([Lam et al., 2015](#)) and SciPy ([Virtanen et al., 2020](#)). Figures were plotted using matplotlib ([Hunter, 2007](#)). The package is available under BSD3 license at <https://github.com/qb3/sparse-ho>, with documentation and examples available at <https://qb3.github.io/sparse-ho/>. Online code includes scripts to reproduce all figures and experiments of the paper.

### 4.1 Hypergradient computation

*Comparison with alternative approaches* ([Figure 4](#)). First, we compare different methods to compute the hypergradient:

- Forward-mode differentiation of proximal coordinate descent ([Algorithm 3](#)).
- Reverse-mode differentiation of proximal coordinate descent ([Algorithm 4](#)).
- `cvxpylayers` ([Agrawal et al., 2019](#)), a software based on `cvxpy` ([Diamond and Boyd, 2016](#)), solving *disciplined parametrized programming* and providing derivatives with respect to the parameters of the program. It is thus possible to use `cvxpylayers` to compute gradients with respect to the regularization parameters.

[Figure 4](#) compares the time taken by multiple methods to compute a single hypergradient  $\nabla \mathcal{L}(\lambda)$  for the Lasso (see [Table 1](#)), for multiple values of  $\lambda$ . It shows the time taken to

Table 5: Characteristics of the data sets used for the experiments.

name	# samples $n$	# features $p$	# classes $q$	density
<i>breast cancer</i>	569	30	—	1
<i>diabetes</i>	442	10	—	1
<i>leukemia</i>	72	7,129	—	1
<i>gina agnostic</i>	3,468	970	—	1
<i>rcv1</i>	20,242	19,960	—	$3.7 \times 10^{-3}$
<i>real-sim</i>	72,309	20,958	—	$2.4 \times 10^{-3}$
<i>news20</i>	19,996	632,983	—	$6.1 \times 10^{-4}$
<i>mnist</i>	60,000	683	10	$2.2 \times 10^{-1}$
<i>usps</i>	7,291	256	10	1
<i>rcv1 (multiclass)</i>	15,564	16,245	53	$4.0 \times 10^{-3}$
<i>aloi</i>	108,000	128	1,000	$2.4 \times 10^{-1}$

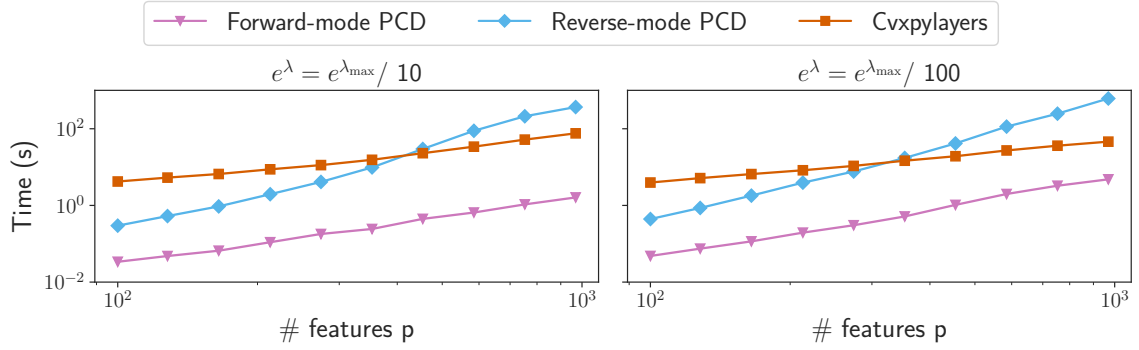


Figure 4: *Lasso with hold-out criterion*: time comparison on the *gina* data set to compute a single hypergradient as a function of the number of features, for two values of  $\lambda$ ,  $e^\lambda = e^{\lambda_{\max}}/10$  (left) and  $e^\lambda = e^{\lambda_{\max}}/100$  (right).

compute the regression coefficients and the hypergradient, as a function of the number of columns, sampled from the design matrix from the *gina* data set. The columns were selected at random and 10 repetitions were performed for each point of the curves. In order to aim for good numerical precision, problems were solved up to a duality gap of  $10^{-6}$  for the forward-mode and the reverse-mode. `cvxpylayers` relies on `cvxpy`, solving [Problem \(1\)](#) using a splitting conic solver ([O’Donoghue et al., 2019](#)). Since the termination criterion of the splitting conic solver is not exactly the duality gap ([O’Donoghue et al., 2016](#), Sec. 3.5), we used the default tolerance of  $10^{-4}$ . The hypergradient  $\nabla \mathcal{L}(\lambda)$  was computed for hold-out mean squared error (see [Table 2](#)).

The forward-mode differentiation of proximal coordinate descent is one order of magnitude faster than `cvxpylayers` and two orders of magnitude faster than the reverse-mode

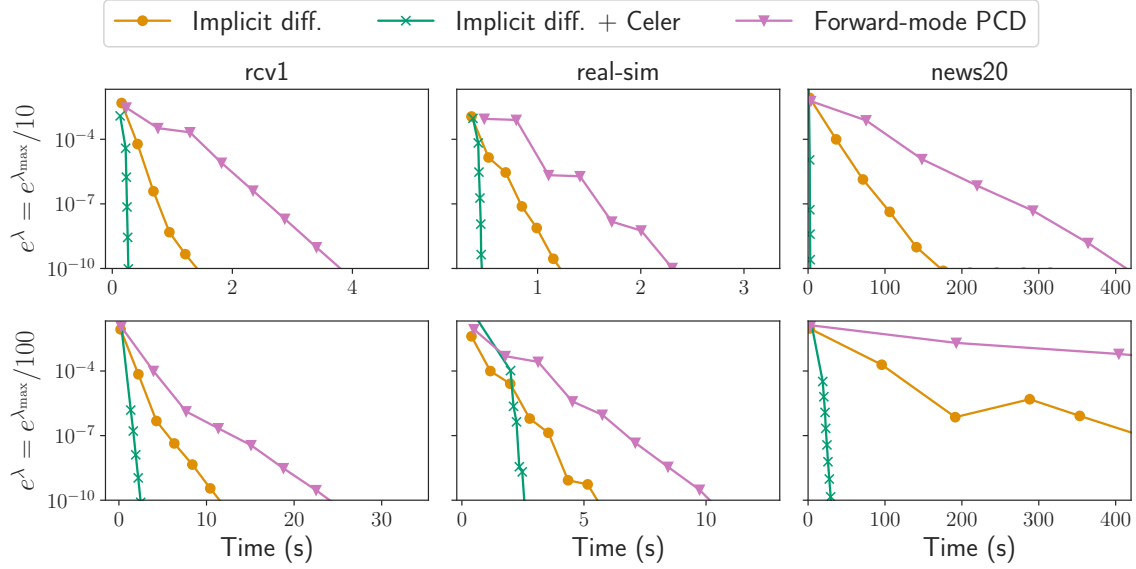


Figure 5: *Lasso with hold-out criterion*: absolute difference between the exact hypergradient (using  $\hat{\beta}$ ) and the iterate hypergradient (using  $\beta^{(k)}$ ) of the Lasso as a function of time. Results are for three data sets and two different regularization parameters. “Implicit diff. + Celer” uses **Celer** (Massias et al., 2020) instead of our proximal coordinate descent implementation.

differentiation of proximal coordinate descent. The larger the value of  $\lambda$ , the sparser the coefficients  $\beta$  are, leading to significant speedups in this regime. This performance is in accordance with the lower time cost of the forward mode in Table 4.

*Combining implicit differentiation with state-of-the art solvers* (Figures 5 and 6). We now compare the different approaches described in Section 3:

- Forward-mode differentiation of proximal coordinate descent (Algorithm 3).
- Implicit differentiation (Algorithm 5) with proximal coordinate descent to solve the inner problem. For efficiency, this solver was coded in Numba (Lam et al., 2015).
- Implicit differentiation (Algorithm 5) with state-of-the-art algorithm to solve the inner problem: we used **Celer** (Massias et al., 2020) for the Lasso, and **Lightning** (Blondel and Pedregosa, 2016) for the SVM.

Figure 5 shows for three data sets and two values of regularization parameters the absolute difference between the exact hypergradient and the approximate hypergradient obtained via multiple algorithms as a function of time. Figure 6 reports similar results for the SVM, on the same data sets, except *news20*, which is not well suited for SVM, due to limited number of samples.



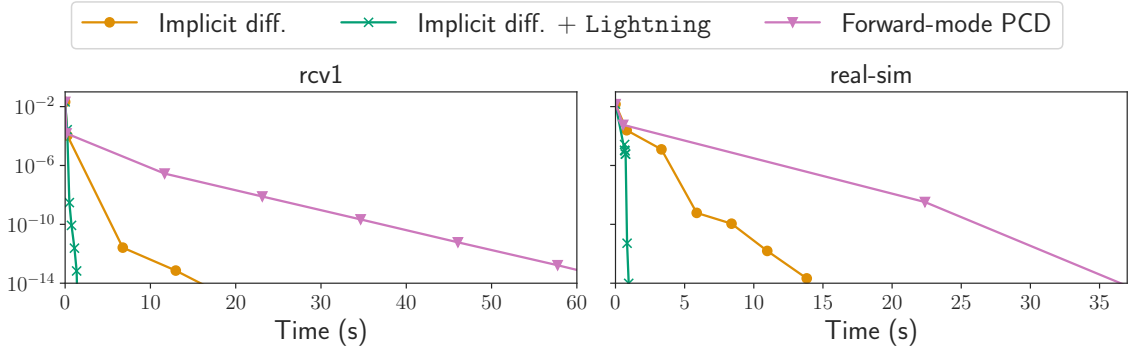


Figure 6: *SVM with hold-out criterion*: absolute difference between the exact hypergradient (using  $\hat{\beta}$ ) and the iterate hypergradient (using  $\beta^{(k)}$ ) of the SVM as a function of time. “Implicit diff. + Lightning” uses **Lightning** (Blondel and Pedregosa, 2016), instead of our proximal coordinate descent implementation.

First, it demonstrates that implicit differentiation methods are faster than the forward-mode of proximal coordinate descent (pink). This illustrates the benefits of restricting the gradient computation to the support of the Jacobian, as described in Section 3.5. Second, thanks to the flexibility of our approach, we obtain additional speed-ups by combining implicit differentiation with a state-of-the-art solver, **Celer**. The resulting method (orange) significantly improves over implicit differentiation using a vanilla proximal coordinate descent (green).

## 4.2 Resolution of the Bilevel Optimization Problem

In this section we compare multiple methods to find the optimal hyperparameters for the Lasso, elastic net and multiclass sparse logistic regression. The following methods are compared:

- *Grid-search*: for the Lasso and the elastic net, the number of hyperparameters is small, and grid-search is tractable. For the Lasso we chose a grid of 100 hyperparameters  $\lambda$ , uniformly spaced between  $\lambda_{\max} - \ln(10^4)$  and  $\lambda_{\max}$ . For the elastic net we chose for each of the two hyperparameters a grid of 10 values uniformly spaced between  $\lambda_{\max}$  and  $\lambda_{\max} - \ln(10^4)$ . The product grid thus has  $10^2$  points.
- *Random-search*: we chose 30 values of  $\lambda$  sampled uniformly between  $\lambda_{\max}$  and  $\lambda_{\max} - \ln(10^4)$  for each hyperparameter. For the elastic net we chose 30 points sampled uniformly in  $[\lambda_{\max} - \ln(10^4), \lambda_{\max}] \times [\lambda_{\max} - \ln(10^4), \lambda_{\max}]$ .
- *SMBO*: this algorithm is SMBO using as criterion expected improvement (EI) and the Tree-structured Parzen Estimator (TPE) as model. First it evaluates  $\mathcal{L}$  using 5 values of  $\lambda$ , chosen uniformly at random between  $\lambda_{\max}$  and  $\lambda_{\max} - \ln(10^4)$ . Then a

TPE model is fitted on the data points  $(\lambda^{(1)}, \mathcal{L}(\lambda^{(1)})), \dots, (\lambda^{(5)}, \mathcal{L}(\lambda^{(5)}))$ . Iteratively, the EI is used to choose the next point to evaluate  $\mathcal{L}$  at, and this value is used to update the model. We used the `hyperopt` implementation (Bergstra et al., 2013).

- *1st order*: first-order method with exact gradient (Algorithm 6 with constant tolerances  $\epsilon_i = 10^{-6}$ ), with  $\lambda_{\max} - \ln(10^2)$  as a starting point.
- *1st order approx*: a first-order method using approximate gradient (Algorithm 6 with tolerances  $\epsilon_i$ , geometrically decreasing from  $10^{-2}$  to  $10^{-6}$ ), with  $\lambda_{\max} - \ln(10^2)$  as a starting point.

*Outer criterion.* In the Lasso and elastic net experiments, we pick a  $K$ -fold CV loss as outer criterion<sup>6</sup>. Hence, the data set  $(X, y)$  is partitioned into  $K$  hold-out data sets  $(X^{\text{train}_k}, y^{\text{train}_k}), (X^{\text{val}_k}, y^{\text{val}_k})$ . The bilevel optimization problems then write

$$\begin{aligned} \arg \min_{\lambda=(\lambda_1, \lambda_2) \in \mathbb{R}^2} \mathcal{L}(\lambda) &= \frac{1}{K} \sum_{k=1}^K \|y^{\text{val}_k} - X^{\text{val}_k} \hat{\beta}^{(\lambda, k)}\|_2^2 \\ \text{s.t. } \hat{\beta}^{(\lambda, k)} &\in \arg \min_{\beta \in \mathbb{R}^p} \frac{1}{2n} \|y^{\text{train}_k} - X^{\text{train}_k} \beta\|_2^2 + e^{\lambda_1} \|\beta\|_1 + \frac{e^{\lambda_2}}{2} \|\beta\|_2^2, \quad \forall k \in [K], \end{aligned} \quad (17)$$

while Lasso CV is obtained taking  $\lambda_2 \rightarrow -\infty$  in the former. By considering an extended variable  $\beta \in \mathbb{R}^{K \times p}$ , cross-validation can be cast as an instance of Problem (2).

Figure 7 represents the cross-validation loss in Lasso CV as a function of the regularization parameter  $\lambda$  (black curve, three top rows) and as a function of time (bottom). Each point corresponds to the evaluation of the cross-validation criterion for one  $\lambda$  value. The top rows show cross-validation loss as a function of  $\lambda$ , for the grid-search, the SMBO optimizer and the first-order method. The lightest crosses correspond to the first iterations of the algorithm and the darkest, to the last ones. For instance, Lasso grid-search starts to evaluate the cross-validation function with  $\lambda = \lambda_{\max}$  and then decreases to  $\lambda = \lambda_{\max} - \ln(10^4)$ . On all the data sets, first-order methods are faster to find the optimal regularization parameter, requiring only 5 iterations.

Figure 8 represents the level sets of the cross-validation loss for the elastic net (three top rows) and the cross-validation loss as a function of time (bottom). One can see that after 5 iterations the SMBO algorithm (blue crosses) suddenly slows down (bottom) as the hyperparameter suggested by the algorithm leads to a costly optimization problem to solve, while first-order methods converge quickly as for Lasso CV. In the present context, inner problems are slower to solve for low values of the regularization parameters.

*Multiclass sparse logistic regression (# classes hyperparameters, Figure 9).* We consider a multiclass classification problem with  $q$  classes. The design matrix is noted  $X \in \mathbb{R}^{n \times p}$ , and the target variable  $y \in \{1, \dots, q\}^n$ . We chose to use a one-versus-all model with  $q$

6. In our experiments the default choice is  $K = 5$ .

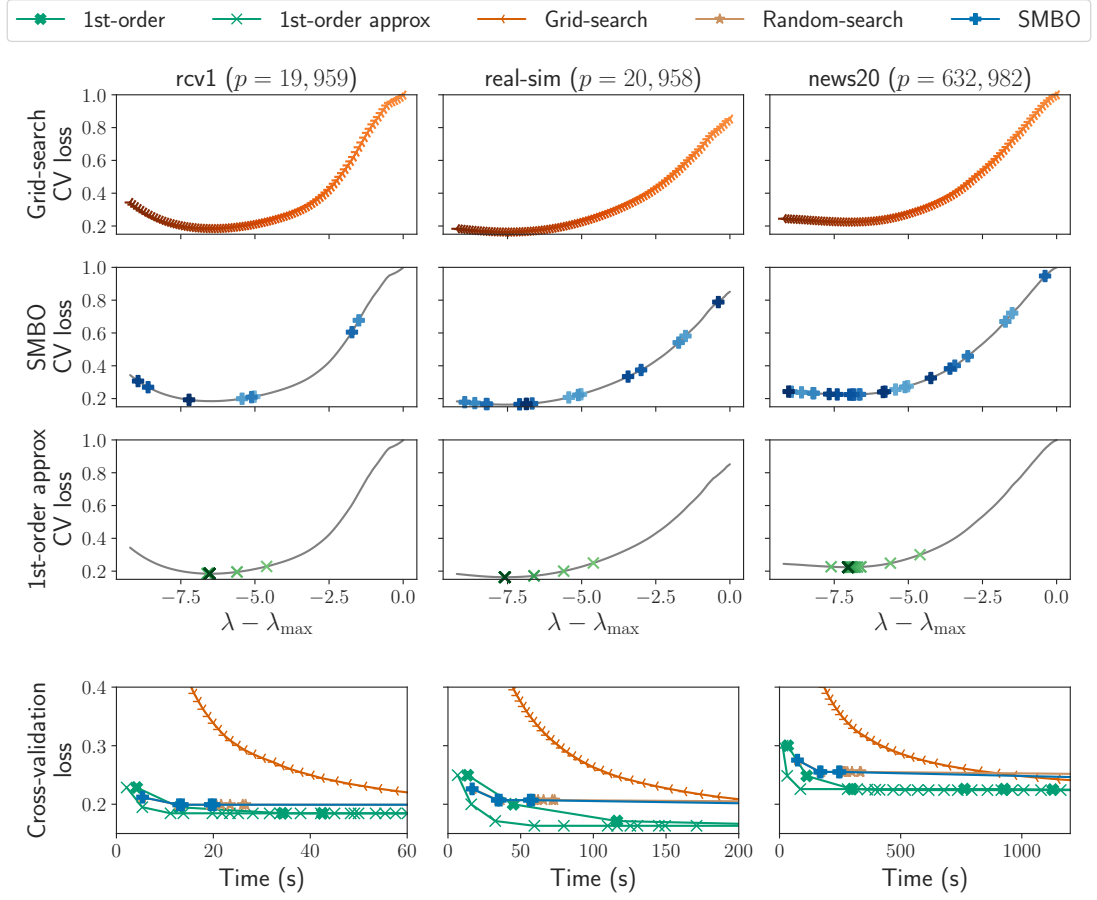


Figure 7: *Lasso with cross-validation criterion*: cross-validation loss as a function of  $\lambda$  (black line, top) and as a function of time (bottom). Lighter markers correspond to earlier iterations of the algorithm.

regularization parameters. We use a binary cross-entropy for the inner loss

$$\psi^k(\beta, \lambda_k; X, y) \triangleq -\frac{1}{n} \sum_{i=1}^n (\mathbb{1}_{y_i=k} \ln(\sigma(X_i; \beta)) + (1 - \mathbb{1}_{y_i=k}) \ln(1 - \sigma(X_i; \beta))) + e^{\lambda_k} \|\beta\|_1, \quad (18)$$

and a multiclass cross-entropy for the outer criterion

$$\mathcal{C}(\hat{\beta}^{(\lambda_1)}, \dots, \hat{\beta}^{(\lambda_q)}; X, y) \triangleq -\sum_{i=1}^n \sum_{k=1}^q \ln \left( \frac{e^{X_i; \hat{\beta}^{(\lambda_k)}}}{\sum_{l=1}^q e^{X_i; \hat{\beta}^{(\lambda_l)}}} \right) \mathbb{1}_{y_i=k}. \quad (18)$$

With a single train/test split, the bilevel problem to solve writes:

$$\begin{aligned} \arg \min_{\lambda \triangleq (\lambda_1, \dots, \lambda_q) \in \mathbb{R}^q} \quad & \mathcal{C}(\hat{\beta}^{(\lambda_1)}, \dots, \hat{\beta}^{(\lambda_q)}; X^{\text{test}}, y^{\text{test}}) \\ \text{s.t.} \quad & \hat{\beta}^{(\lambda_k)} \in \arg \min_{\beta \in \mathbb{R}^p} \psi^k(\beta, \lambda_k; X^{\text{train}}, y^{\text{train}}) \quad \forall k \in [q] . \end{aligned} \quad (19)$$

Figure 9 represents the multiclass cross-entropy (top), the accuracy on the validation set (middle) and the accuracy on the test set (unseen data, bottom). When the number of hyperparameter is moderate ( $q = 10$ , on *mnist* and *usps*), the multiclass cross-entropy reached by SMBO and random techniques is as good as first-order techniques. This is expected and follows the same conclusion as [Bergstra and Bengio \(2012\)](#); [Frazier \(2018\)](#): when the number of hyperparameters is moderate, SMBO and random techniques can be used efficiently. However, when the number of hyperparameters increases (*rcv1*,  $q = 53$  and *aloi*,  $q = 1000$ ), the hyperparameter space is too large: zero-order solvers simply fail. On the contrary, first-order techniques manage to find hyperparameters leading to significantly better accuracy.

**Remark 19** *On the data used in Figure 9, the model with one hyperparameter per class did not yield significantly better test accuracy compared to a multiclass logistic regression with only one regularization hyperparameter for all the classes. This may mean that the model with one hyperparameter per class is not well suited for this data. It can also be due to the fact that in this case, the bilevel optimization problem becomes highly non-convex, and only converges toward a poor local minima. We want to emphasize that we provide an efficient way to compute the hypergradient  $\nabla_{\lambda} \mathcal{L}(\lambda)$ . Besides, to our knowledge, the perfect resolution of the full bilevel optimization problem with a non-smooth inner problem remains an open question.*

## 5. Conclusion

In this work we considered the problem of hyperparameter optimization to select the regularization parameter of linear models with non-smooth objective. Casting this problem as a bilevel optimization problem, we proposed to use first-order methods. We showed that the usual automatic differentiation techniques, implicit differentiation, forward and reverse modes, can be used to compute the hypergradient, despite the non-smoothness of the inner problem. Experimentally, we showed the interest of first-order techniques to solve bilevel optimization on a wide range of estimators ( $\ell_1$  penalized methods, SVM, etc.) and data sets. The presented techniques could also be extended to more general bilevel optimization problems, in particular implicit differentiation could be well suited for meta-learning problems, with a potentially large number of hyperparameters. Another important future direction would be to extend the work on stochastic hypergradients ([Grazzi et al., 2021](#)) in the non-smooth case.

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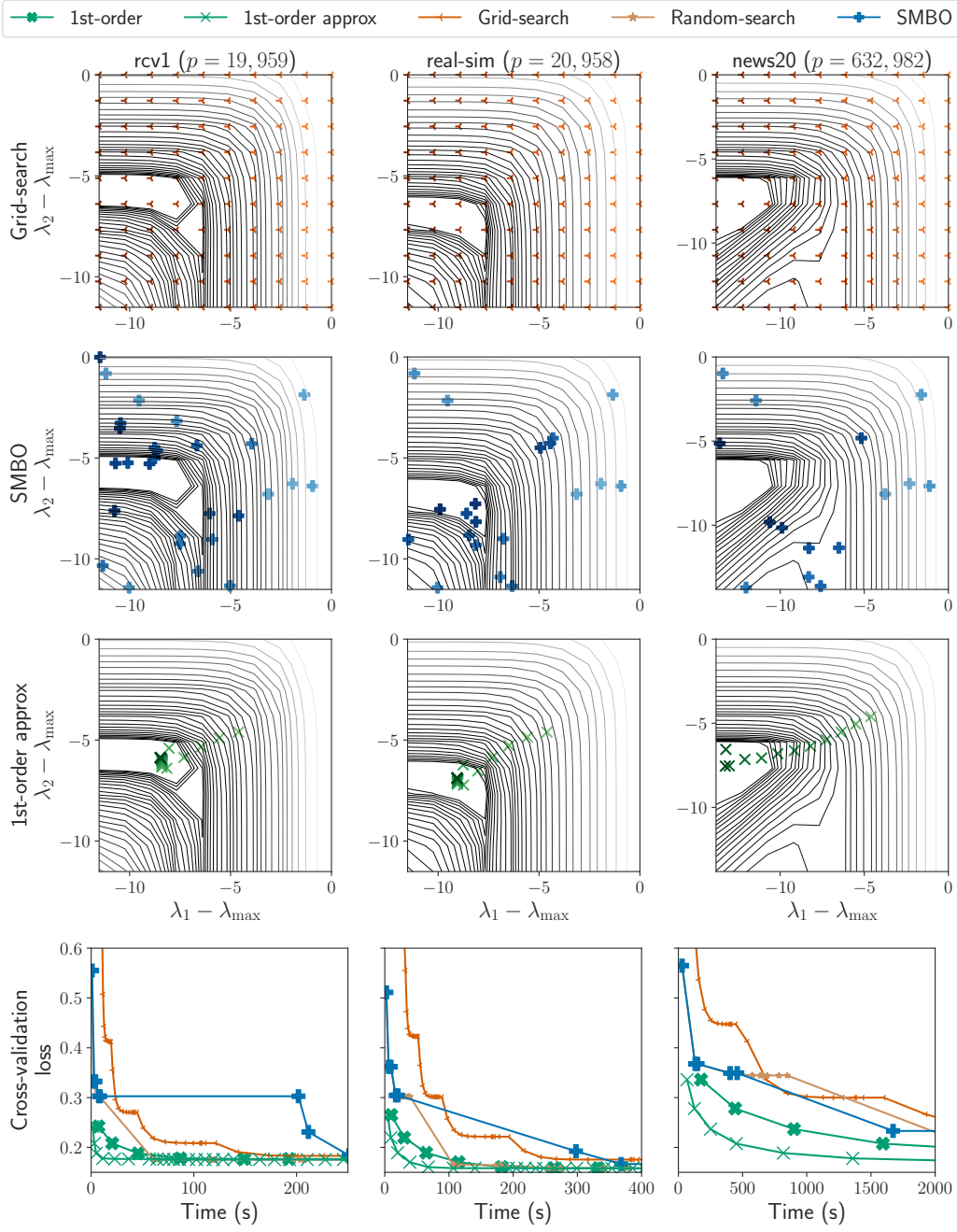


Figure 8: **Elastic net cross-validation, time comparison (2 hyperparameters).** Level sets of the cross-validation loss (black lines, top) and cross-validation loss as a function of time (bottom) on *rcv1*, *real-sim* and *news20* data sets.

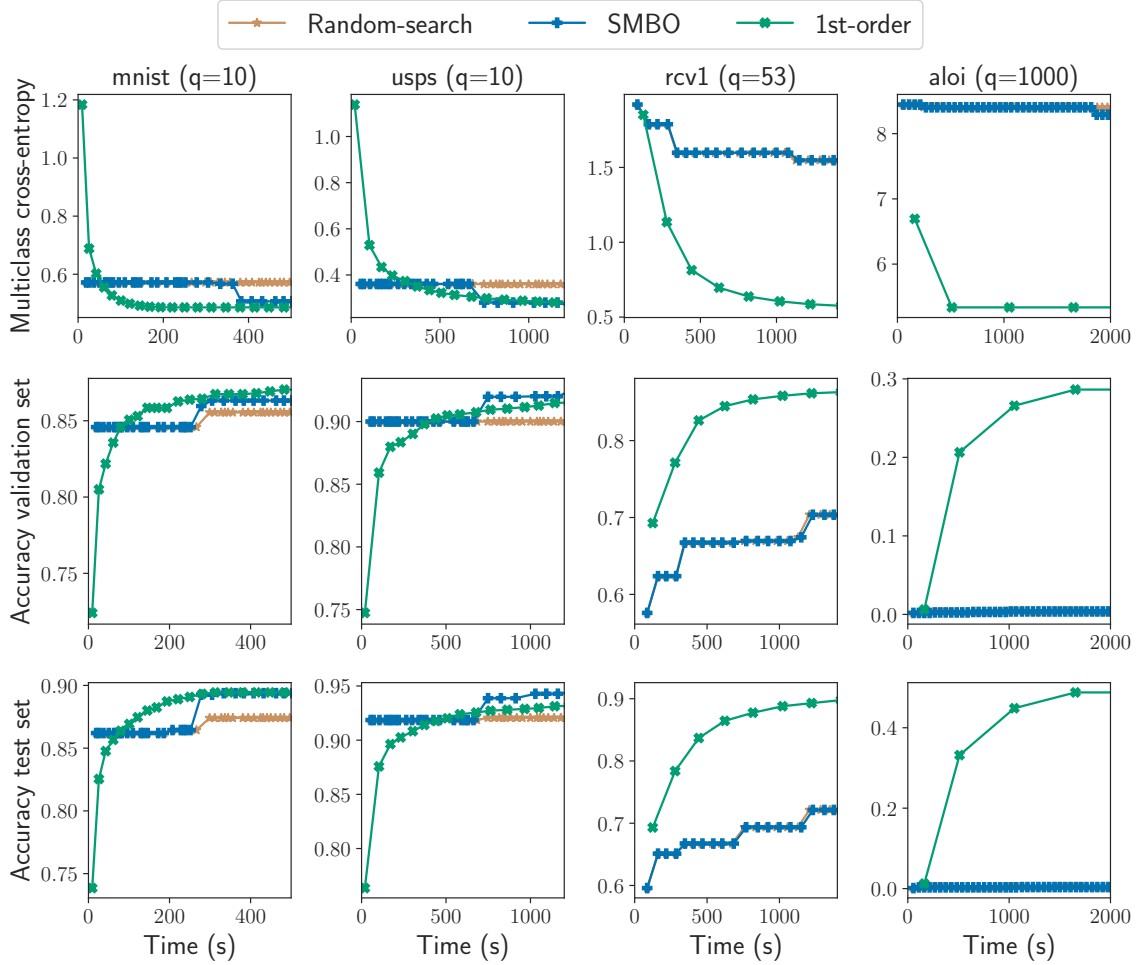


Figure 9: **Multiclass sparse logistic regression hold-out, time comparison (# classes hyperparameters)**. Multiclass cross-entropy (top), accuracy on the validation set (middle), and accuracy on the test set (bottom) as a function of time on *mnist*, *usps* ( $q = 10$  classes), *rcv1* ( $q = 53$  classes), *aloι* ( $q = 1000$  classes).



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## A. Implicit Differentiation Examples

For exposition purpose we provide instantiations of the implicit differentiation ([Algorithm 5](#)) for multiple optimization problems. For the Lasso ([Algorithm 7](#))

$$\hat{\beta} \in \arg \min_{\beta \in \mathbb{R}^p} \frac{1}{n} \|y - X\beta\|^2 + e^\lambda \|\beta\|_1 ,$$

the elastic net ([Algorithm 8](#))

$$\hat{\beta} \in \arg \min_{\beta \in \mathbb{R}^p} \frac{1}{n} \|y - X\beta\|^2 + e^{\lambda_1} \|\beta\|_1 + e^{\lambda_2} \|\beta\|_2^2 ,$$

the weighted Lasso ([Algorithm 9](#))

$$\hat{\beta} \in \arg \min_{\beta \in \mathbb{R}^p} \frac{1}{n} \|y - X\beta\|^2 + \sum_{j=1}^p e^{\lambda_j} |\beta_j| ,$$

and the dual of the SVM

$$\hat{w} \in \arg \min_{w \in \mathbb{R}^n} \frac{1}{2} w^\top (y \odot X)(y \odot X)^\top w^\top - w^\top \mathbf{1} + \sum_{i=1}^n \iota_{0 \leq w_i \leq e^\lambda} .$$

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**Algorithm 7** LASSO IMPLICIT DIFFERENTIATION
 

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**input** :  $\lambda \in \mathbb{R}, \epsilon > 0$   
 // compute the solution of inner problem  
 Find  $\beta$  such that:  $\Phi(\beta, \lambda) - \Phi(\hat{\beta}, \lambda) \leq \epsilon$   
 // compute the gradient  
 $S = \{j \in [p] : \beta_j \neq 0\}; A = \frac{1}{n} X_{:,S}^\top X_{:,S}$   
 Find  $v \in \mathbb{R}^{|S|}$  s.t.  $\|A^{-1} \nabla_S \mathcal{C}(\beta) - v\| \leq \epsilon$   
 $B = -e^\lambda \text{sign}(\beta_S) \in \mathbb{R}^{|S|}$   
 $\nabla \mathcal{L}(\lambda) = v^\top B \in \mathbb{R}$   
**return**  $\mathcal{L}(\lambda) \triangleq \mathcal{C}(\beta), \nabla \mathcal{L}(\lambda)$

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**Algorithm 8** ELASTIC NET IMPLICIT DIFFERENTIATION
 

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**input** :  $\lambda_1, \lambda_2 \in \mathbb{R}, \epsilon > 0$   
 // compute the solution of inner problem  
 Find  $\beta$  such that:  $\Phi(\beta, \lambda) - \Phi(\hat{\beta}, \lambda) \leq \epsilon$   
 // compute the gradient  
 $S = \{j \in [p] : \beta_j \neq 0\}; A = \frac{1}{n} X_{:,S}^\top X_{:,S}$   
 Find  $v \in \mathbb{R}^{|S|}$  s.t.  $\|A^{-1} \nabla_S \mathcal{C}(\beta) - v\| \leq \epsilon$   
 $B = -[e^{\lambda_1} \text{sign}(\beta_S), e^{\lambda_2} \beta_S] \in \mathbb{R}^{|S| \times 2}$   
 $\nabla \mathcal{L}(\lambda) = v^\top B \in \mathbb{R}^2$   
**return**  $\mathcal{L}(\lambda) \triangleq \mathcal{C}(\beta), \nabla \mathcal{L}(\lambda)$

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**Algorithm 9** WEIGHTED LASSO IMPLICIT DIFFERENTIATION
 

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**input** :  $\lambda \in \mathbb{R}^p, \epsilon > 0$   
 // compute the solution of inner problem  
 Find  $\beta$  such that:  $\Phi(\beta, \lambda) - \Phi(\hat{\beta}, \lambda) \leq \epsilon$   
 // compute the gradient  
 $S = \{j \in [p] : \beta_j \neq 0\}; A = \frac{1}{n} X_{:,S}^\top X_{:,S}$   
 Find  $v \in \mathbb{R}^{|S|}$  s.t.  $\|A^{-1} \nabla_S \mathcal{C}(\beta) - v\| \leq \epsilon$   
 $B = -\text{diag}(e^{\lambda_j} \text{sign}(\beta_j)) \in \mathbb{R}^{|S| \times |S|}$   
 $\nabla \mathcal{L}(\lambda) = v^\top B \in \mathbb{R}^p$   
**return**  $\mathcal{L}(\lambda) \triangleq \mathcal{C}(\beta), \nabla \mathcal{L}(\lambda)$

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**Algorithm 10** SVM DUAL IMPLICIT DIFFERENTIATION
 

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**input** :  $\lambda \in \mathbb{R}, \epsilon > 0$   
**init** :  $\mathcal{J} = 0_{\mathbb{R}^p}$   
 // compute the solution of inner problem  
 Find  $w$  such that:  $\Phi(w, \lambda) - \Phi(\hat{w}, \lambda) \leq \epsilon$   
 // compute the gradient  
 $S_0 \triangleq \{i \in [n] : w_i = 0\}; \mathcal{J}_{S_0} = 0$   
 $S_\lambda \triangleq \{i \in [n] : w_i = e^\lambda\}; \mathcal{J}_{S_\lambda} = e^\lambda$   
 $S = \{i \in [n] : w_i \neq 0 \text{ and } w_i \neq e^\lambda\}$   
 $A = (y \odot X)_{S,:} (y \odot X)_{S,:}^\top$   
 Find  $v \in \mathbb{R}^{|S|}$  s.t.  $\|A^{-1} \nabla_S \mathcal{C}(w) - v\| \leq \epsilon$   
 $B = (y \odot X)_{S,:} (y \odot X)_{S_\lambda,:}^\top \mathcal{J}_{S_\lambda}$   
 $\nabla \mathcal{L}(\lambda) = \mathcal{J}_{S_\lambda}^\top \nabla_S \mathcal{C}(w) + v^\top B$   
**return**  $\mathcal{L}(\lambda) \triangleq \mathcal{C}(\beta), \nabla \mathcal{L}(\lambda)$

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## B. Additional Lemmas

### B.1 Differentiability of the Proximal Operator

Here we recall results on the differentiability of the proximal operator at the optimum.

**Lemma 20** (Klopfenstein et al. 2020, Lemmas 2 and 3) *Let  $0 < \gamma_j \leq 1/L_j$ . Let  $\lambda \in \mathbb{R}^r$  and  $\Lambda$  a neighborhood of  $\lambda$ . Consider a solution  $\hat{\beta} \in \arg \min_{\beta \in \mathbb{R}^p} \Phi(\beta, \lambda)$  and  $\hat{S}$  its generalized support. Suppose*

1. Assumptions 2, 3 and 6 hold.
2. Assumption 4 hold on  $\Lambda$ .

Then, for all  $j \in \hat{S}$ , the map  $\beta \mapsto \text{prox}_{\gamma_j g_j(\cdot, \lambda)}$  is differentiable at  $\hat{\beta}_{\hat{S}}$ . Moreover, for all  $j \in \hat{S}^c$ ,  $\text{prox}_{\gamma_j g_j(\cdot, \lambda)}$  is constant around  $\hat{\beta}_j - \gamma_j \nabla_j f(\hat{\beta})$ . Thus,  $\beta \mapsto \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(\beta_j - \gamma_j \nabla_j f(\beta))$  is differentiable at  $\hat{\beta}$  with gradient 0.

## B.2 Linear Convergence

We now detail the following result: an asymptotic vector autoregressive sequence, with an error term vanishing linearly to 0, converges linearly to its limit. In a more formal way:

**Lemma 21** *Let  $A \in \mathbb{R}^{p \times p}$ ,  $b \in \mathbb{R}^p$  with  $\rho(A) < 1$ . Let  $(\mathcal{J}^{(k)})_{k \in \mathbb{N}}$  be a sequence of  $\mathbb{R}^p$  such that*

$$\mathcal{J}^{(k+1)} = A\mathcal{J}^{(k)} + b + \epsilon^{(k)} , \quad (20)$$

*with  $(\epsilon^{(k)})_{k \in \mathbb{N}}$  a sequence which converges linearly to 0, then  $(\mathcal{J}^{(k)})_{k \in \mathbb{N}}$  converges linearly to its limit  $\hat{\mathcal{J}} \triangleq (\text{Id} - A)^{-1}b$ .*

**Proof** Assume  $(\epsilon^{(k)})_{k \in \mathbb{N}}$  converges linearly. Then, there exists  $c_1 > 0, 0 < \nu < 1$  such that

$$\|\epsilon^{(k)}\| \leq c_1 \nu^k .$$

Applying a standard result on spectral norms (see [Polyak 1987](#), Chapter 2, Lemma 1) yields a bound on  $\|A^k\|_2$ . More precisely, for every  $\delta > 0$  there is a constant  $c_2(\delta) = c_2$  such that

$$\|A^k\|_2 \leq c_2(\rho(A) + \delta)^k .$$

Without loss of generality, we consider from now on a choice of  $\delta$  such that  $\rho(A) + \delta < 1$ . Since  $\hat{\mathcal{J}} = (\text{Id} - A)^{-1}b$  the limit  $\hat{\mathcal{J}}$  of the sequence satisfies

$$\hat{\mathcal{J}} = A\hat{\mathcal{J}} + b . \quad (21)$$

Taking the difference between [Equations \(20\)](#) and [\(21\)](#) yields:

$$\mathcal{J}^{(k+1)} - \hat{\mathcal{J}} = A(\mathcal{J}^{(k)} - \hat{\mathcal{J}}) + \epsilon^{(k)} . \quad (22)$$

Unrolling [Equation \(22\)](#) yields  $\mathcal{J}^{(k+1)} - \hat{\mathcal{J}} = A^{k+1}(\mathcal{J}^{(0)} - \hat{\mathcal{J}}) + \sum_{k'=0}^k A^{k'} \epsilon^{(k-k')}$ . Taking the norm on both sides and using the triangle inequality leads to

$$\begin{aligned} \|\mathcal{J}^{(k+1)} - \hat{\mathcal{J}}\|_2 &\leq \|A^{k+1}(\mathcal{J}^{(0)} - \hat{\mathcal{J}})\|_2 + \sum_{k'=0}^k \|A^{k'}\|_2 \|\epsilon^{(k-k')}\| \\ &\leq \|A^{k+1}\|_2 \cdot \|\mathcal{J}^{(0)} - \hat{\mathcal{J}}\|_2 + c_1 \sum_{k'=0}^k \|A^{k'}\|_2 \cdot \nu^{k-k'} \\ &\leq c_2(\rho(A) + \delta)^{k+1} \cdot \|\mathcal{J}^{(0)} - \hat{\mathcal{J}}\|_2 + c_1 \sum_{k'=0}^k c_2(\rho(A) + \delta)^{k'} \nu^{k-k'} \end{aligned}$$

We can now split the last summand in two parts and obtain the following bound, reminding that  $\rho(A) + \delta < 1$

$$\begin{aligned}
 \|\mathcal{J}^{(k+1)} - \hat{\mathcal{J}}\|_2 &\leq c_2(\rho(A) + \delta)^{k+1} \cdot \|\mathcal{J}^{(0)} - \hat{\mathcal{J}}\|_2 \\
 &\quad + c_1 c_2 \left( \sum_{k'=0}^{k/2} (\rho(A) + \delta)^{k'} \nu^{k-k'} + \sum_{k'=k/2}^k (\rho(A) + \delta)^{k'} \nu^{k-k'} \right) \\
 &\leq c_2(\rho(A) + \delta)^{k+1} \cdot \|\mathcal{J}^{(0)} - \hat{\mathcal{J}}\|_2 + \frac{c_1 c_2 (\rho(A) + \delta)}{1 - \rho(A) - \delta} \sqrt{\nu}^k \\
 &\quad + \frac{c_1 c_2 \nu}{1 - \nu} \sqrt{(\rho(A) + \delta)^k} .
 \end{aligned}$$

Thus,  $(\mathcal{J}^{(k)})_{k \in \mathbb{N}}$  converges linearly towards its limit  $\hat{\mathcal{J}}$ . ■

### C. Proof of Theorem 12

**Theorem 12** Local linear convergence of the Jacobian. *Let  $0 < \gamma \leq 1/L$ . Suppose Assumptions 2, 3 and 6 hold. Let  $\lambda \in \mathbb{R}^r$ ,  $\Lambda$  be a neighborhood of  $\lambda$ , and  $\Gamma^\Lambda \triangleq \{\hat{\beta}^{(\lambda)} - \gamma \nabla f(\hat{\beta}^{(\lambda)}) : \lambda \in \Lambda\}$ . In addition, suppose hypotheses (H1) to (H4) from Theorem 9 are satisfied and the sequence  $(\beta^{(k)})_{k \in \mathbb{N}}$  generated by Algorithm 1 (respectively by Algorithm 3) converges toward  $\hat{\beta}$ .*

*Then, the sequence of Jacobians  $(\mathcal{J}^{(k)})_{k \geq 0}$  generated by the forward-mode differentiation of proximal gradient descent (Algorithm 1) (respectively by forward-mode differentiation of proximal coordinate descent, Algorithm 3) converges locally linearly towards  $\hat{\mathcal{J}}$ .*

**Proof** We first prove Theorem 12 for proximal gradient descent.

*Proximal gradient descent case.* Solving Problem (1) with proximal gradient descent leads to the following updates:

$$\beta^{(k+1)} = \text{prox}_{\gamma g(\cdot, \lambda)} \left( \underbrace{\beta^{(k)} - \gamma \nabla f(\beta^{(k)})}_{z^{(k)}} \right) . \quad (23)$$

Consider the following sequence  $(\mathcal{J}^{(k)})_{k \in \mathbb{N}}$  defined by

$$\mathcal{J}^{(k+1)} = \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)}) \odot \left( \text{Id} - \gamma \nabla^2 f(\beta^{(k)}) \right) \mathcal{J}^{(k)} + \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)}) . \quad (24)$$

Note that if  $\text{prox}_{\gamma g(\cdot, \lambda)}$  is not differentiable with respect to the first variable at  $z^{(k)}$  (respectively with respect to the second variable  $\lambda$ ), any weak Jacobian can be used. When (H3) holds, differentiating Equation (23) with respect to  $\lambda$  yields exactly Equation (24).

Assumptions 2 to 4 and 6 and the convergence of  $(\beta^{(k)})$  toward  $\hat{\beta}$  ensure proximal gradient descent algorithm has finite identification property (Liang et al., 2014, Thm. 3.1): we note  $K$  the iteration when identification is achieved. As before, the separability of  $g$ , Assumptions 2 to 4 and 6 ensure (see Theorem 20)  $\partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(z^k)_{\hat{S}^c} = 0$ , for all  $k \geq K$ . Thus, for all  $k \geq K$ ,

$$\mathcal{J}_{\hat{S}^c}^{(k)} = \hat{\mathcal{J}}_{\hat{S}^c} = \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)})_{\hat{S}^c} .$$

The updates of the Jacobian then become

$$\mathcal{J}_{\hat{S}}^{(k+1)} = \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)})_{\hat{S}} \odot \left( \text{Id} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\beta^{(k)}) \right) \mathcal{J}_{\hat{S}}^{(k)} + \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(z^{(k)})_{\hat{S}} .$$

From Assumption 6, we have that  $f$  is locally  $\mathcal{C}^3$  at  $\hat{\beta}$ ,  $g(\cdot, \lambda)$  is locally  $\mathcal{C}^2$  at  $\hat{\beta}$  hence  $\text{prox}_{g(\cdot, \lambda)}$  is locally  $\mathcal{C}^2$ . The function  $\beta \mapsto \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\beta - \gamma \nabla f(\beta))_{\hat{S}} \odot (\text{Id} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\beta))$  is differentiable at  $\hat{\beta}$ . Using (H4) we have that  $\beta \mapsto \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(\beta - \gamma \nabla f(\beta))_{\hat{S}}$  is also differentiable at  $\hat{\beta}$ . Using the Taylor expansion of the previous functions yields

$$\mathcal{J}_{\hat{S}}^{(k+1)} = \underbrace{\partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}} \odot \left( \text{Id} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\hat{\beta}) \right)}_A \mathcal{J}_{\hat{S}}^{(k)} + \underbrace{\partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}}}_b + \underbrace{o(\|\beta^{(k)} - \hat{\beta}\|)}_{\epsilon^{(k)}} . \quad (25)$$

Thus, for  $0 < \gamma \leq 1/L$ ,

$$\rho(A) \leq \|A\|_2 \leq \underbrace{\|\partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{z})_{\hat{S}}\|}_{\leq 1 \text{ (non-expansiveness)}} \cdot \underbrace{\|\text{Id} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\hat{\beta})\|_2}_{< 1 \text{ (Assumption 7 and } 0 < \gamma \leq 1/L)} < 1 . \quad (26)$$

The inequality on the derivative of the proximal operator comes from the non-expansiveness of proximal operators. The second inequality comes from Assumption 7 and  $0 < \gamma \leq 1/L$ .

Assumptions 2 to 4, 6 and 7 and the convergence of  $(\beta^{(k)})$  toward  $\hat{\beta}$  ensure  $(\beta^{(k)})_{k \in \mathbb{N}}$  converges locally linearly (Liang et al., 2014, Thm. 3.1). The asymptotic autoregressive sequence in Equation (25),  $\rho(A) < 1$ , and the local linear convergence of  $(\epsilon^{(k)})_{k \in \mathbb{N}}$ , yield our result using Theorem 21.

We now prove Theorem 12 for proximal coordinate descent.

*Proximal coordinate descent.* Compared to proximal gradient descent, the analysis of coordinate descent requires studying functions defined as a the composition of  $p$  applications, each of them only modifying one coordinate.

Coordinate descent updates read as follows

$$\beta_j^{(k, j)} = \text{prox}_{\gamma_j g_j(\cdot, \lambda)} \left( \underbrace{\beta_j^{(k, j-1)} - \gamma_j \nabla_j f(\beta^{(k, j-1)})}_{\triangleq z_j^{(k, j-1)}} \right) . \quad (27)$$

We consider the following sequence

$$\begin{aligned} \mathcal{J}_{j:}^{(k,j)} &= \partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j^{(k,j-1)}) \left( \mathcal{J}_{j:}^{(k,j-1)} - \gamma_j \nabla_{j:}^2 f(\beta^{(k,j-1)}) \mathcal{J}_{j:}^{(k,j-1)} \right) \\ &\quad + \partial_\lambda \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j^{(k,j-1)}) . \end{aligned} \quad (28)$$

Note that if  $\text{prox}_{\gamma_j g_j(\cdot, \lambda)}$  is not differentiable with respect to the first variable at  $z^{(k)}$  (respectively with respect to the second variable  $\lambda$ ), any weak Jacobian can be used. When (H3) holds, differentiating Equation (27) with respect to  $\lambda$  yields exactly Equation (28).

Assumptions 2 to 4 and 6 and the convergence of  $(\beta^{(k)})_{k \in \mathbb{N}}$  toward  $\hat{\beta}$  ensure proximal coordinate descent has finite identification property (Klopfenstein et al., 2020, Thm. 1): we note  $K$  the iteration when identification is achieved. Once the generalized support  $\hat{S}$  (of cardinality  $\hat{s}$ ) has been identified, we have that for all  $k \geq K$ ,  $\beta_{\hat{S}^c}^{(k)} = \hat{\beta}_{\hat{S}^c}$  and for any  $j \in \hat{S}^c$ ,  $\partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j^{(k,j-1)}) = 0$ . Thus  $\mathcal{J}_{j:}^{(k,j)} = \partial_\lambda \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j^{(k,j-1)})$ . Then, we have that for any  $j \in \hat{S}$  and for all  $k \geq K$ :

$$\begin{aligned} \mathcal{J}_{j:}^{(k,j)} &= \partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j^{(k,j-1)}) \left( \mathcal{J}_{j:}^{(k,j-1)} - \gamma_j \nabla_{j, \hat{S}}^2 f(\beta^{(k,j-1)}) \mathcal{J}_{\hat{S}:}^{(k,j-1)} \right) \\ &\quad + \partial_\lambda \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j^{(k,j-1)}) - \gamma_j \partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(z_j^{(k,j-1)}) \nabla_{j, \hat{S}^c}^2 f(\beta^{(k,j-1)}) \mathcal{J}_{\hat{S}^c:}^{(k,j-1)} . \end{aligned}$$

Let  $e_1, \dots, e_{\hat{s}}$  be the vectors of the canonical basis of  $\mathbb{R}^{\hat{s}}$ . We can consider the applications

$$\begin{aligned} \mathbb{R}^p &\rightarrow \mathbb{R}^{\hat{s}} \\ \beta &\mapsto \partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(\beta_j - \gamma_j \nabla_j f(\beta)) \left( e_j - \gamma_j \nabla_{j, \hat{S}}^2 f(\beta) \right) , \end{aligned}$$

and

$$\begin{aligned} \mathbb{R}^p &\rightarrow \mathbb{R}^{\hat{s} \times r} \\ \beta &\mapsto \partial_\lambda \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(\beta_j - \gamma_j \nabla_j f(\beta)) - \gamma_j \partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(\beta_j - \gamma_j \nabla_j f(\beta)) \nabla_{j, \hat{S}^c}^2 f(\beta) \hat{\mathcal{J}}_{\hat{S}^c:} , \end{aligned}$$

which are both differentiable at  $\hat{\beta}$  using Assumption 6 and (H4). The Taylor expansion of the previous functions yields:

$$\begin{aligned} \mathcal{J}_{j:}^{(k,j)} &= \partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(\hat{z}_j) \left( e_j - \gamma_j \nabla_{j, \hat{S}}^2 f(\hat{\beta}) \right) \mathcal{J}_{\hat{S}:}^{(k,j-1)} \\ &\quad + \partial_\lambda \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(\hat{z}_j) - \gamma_j \partial_z \text{prox}_{\gamma_j g_j(\cdot, \lambda)}(\hat{z}_j) \nabla_{j, \hat{S}^c}^2 f(\hat{\beta}) \mathcal{J}_{\hat{S}^c:}^{(k,j-1)} \\ &\quad + o(\|\beta^{(k,j-1)} - \hat{\beta}\|) . \end{aligned}$$

Let  $j_1, \dots, j_{\hat{s}}$  be the indices of the generalized support of  $\hat{\beta}$ . When considering a full epoch of coordinate descent, the Jacobian is obtained as the product of matrices of the form

$$A_s^\top = ( e_1 \mid \dots \mid e_{s-1} \mid v_{j_s} \mid e_{s+1} \mid \dots \mid e_{\hat{s}} ) \in \mathbb{R}^{\hat{s} \times \hat{s}} ,$$

where  $v_{j_s} = \partial_z \text{prox}_{\gamma_{j_s} g_{j_s}}(\hat{z}_{j_s}) \left( e_s - \gamma_{j_s} \nabla_{j_s, \hat{S}}^2 f(\hat{\beta}) \right) \in \mathbb{R}^{\hat{S}}$ . A full epoch can then be written

$$\mathcal{J}_{\hat{S}}^{(k+1)} = \underbrace{A_{\hat{S}} A_{\hat{S}-1} \dots A_1}_A \mathcal{J}_{\hat{S}}^{(k)} + b + \epsilon^{(k)} ,$$

for a certain  $b \in \mathbb{R}^{\hat{S}}$ .

The spectral radius of  $A$  is strictly bounded by 1 (Klopfenstein et al., 2020, Lemma 8):  $\rho(A) < 1$ . Assumptions 2 to 4 and 6 and the convergence of  $(\beta^{(k)})_{k \in \mathbb{N}}$  toward  $\hat{\beta}$  ensure local linear convergence of  $(\beta^{(k)})_{k \in \mathbb{N}}$  (Klopfenstein et al., 2020, Thm. 2). Hence, we can write the update for the Jacobian after an update of the coordinates from 1 to  $p$

$$\mathcal{J}_{\hat{S}}^{(k+1)} = A \mathcal{J}_{\hat{S}}^{(k)} + b + \epsilon^{(k)} , \quad (29)$$

with  $(\epsilon^{(k)})_{k \in \mathbb{N}}$  converging linearly to 0.

Recalling  $\rho(A) < 1$ , Theorem 21 and the last display yield our result using.  $\blacksquare$

### C.1 Proof of Theorem 13 (Approximate Hypergradients)

**Theorem 13** Bound on the error of approximate hypergradient. *For  $\lambda \in \mathbb{R}^r$ , let  $\hat{\beta}^{(\lambda)} \in \mathbb{R}^p$  be the exact solution of the inner Problem (1), and  $\hat{S}$  its generalized support. Suppose Assumptions 2, 3 and 6 hold. Let  $\Lambda$  be a neighborhood of  $\lambda$ , and  $\Gamma^\Lambda \triangleq \left\{ \hat{\beta}^{(\lambda)} - \gamma \nabla f(\hat{\beta}^{(\lambda)}) : \lambda \in \Lambda \right\}$ . Suppose hypotheses (H1) to (H4) from Theorem 9 are satisfied. In addition suppose*

(H5) *The application  $\beta \mapsto \nabla^2 f(\beta)$  is Lipschitz continuous.*

(H6) *The criterion  $\beta \mapsto \nabla \mathcal{C}(\beta)$  is Lipschitz continuous.*

(H7) *Both optimization problems in Algorithm 5 are solved up to precision  $\epsilon$  with support identification:  $\|\beta^{(\lambda)} - \hat{\beta}^{(\lambda)}\| \leq \epsilon$ ,  $A^\top$  is invertible, and  $\|A^{-1\top} \nabla_{\hat{S}} \mathcal{C}(\beta^{(\lambda)}) - v\| \leq \epsilon$ .*

*Then the error on the approximate hypergradient  $h$  returned by Algorithm 5 is of the order of magnitude of the error  $\epsilon$  on  $\beta^{(\lambda)}$  and  $v$*

$$\|\nabla \mathcal{L}(\lambda) - h\| = \mathcal{O}(\epsilon) .$$

**Proof Overview of the proof.** Our goal is to bound the error between the approximate hypergradient  $h$  returned by Algorithm 5 and the true hypergradient  $\nabla \mathcal{L}(\lambda)$ . Following the analysis of Pedregosa (2016), two sources of approximation errors arise when computing the hypergradient:



- Approximation errors from the inexact computation of  $\hat{\beta}$ . Dropping the dependency with respect to  $\lambda$ , we denote  $\beta$  the approximate solution and suppose the problem is solved to precision  $\epsilon$  with support identification (H7)

$$\begin{cases} \beta_{\hat{S}^c} = \hat{\beta}_{\hat{S}^c} \\ \|\beta_{\hat{S}} - \hat{\beta}_{\hat{S}}\| \leq \epsilon . \end{cases}$$

- Approximation errors from the approximate resolution of the linear system, using (H7) yields:

$$\|A^{-1\top} \nabla_{\hat{S}} \mathcal{C}(\beta) - v\| \leq \epsilon .$$

The exact solution of the exact linear system  $\hat{v}$  satisfies

$$\hat{v} = \hat{A}^{-1\top} \nabla_{\hat{S}} \mathcal{C}(\hat{\beta}) ,$$

with

$$\begin{aligned} A &\triangleq \text{Id}_{|\hat{S}|} - \underbrace{\partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\beta - \gamma \nabla f(\beta))_{\hat{S}}}_{\triangleq C} \underbrace{\left( \text{Id}_{|\hat{S}|} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\beta) \right)}_{\triangleq D} , \\ \hat{A} &\triangleq \text{Id}_{|\hat{S}|} - \underbrace{\partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{\beta} - \gamma \nabla f(\hat{\beta}))_{\hat{S}}}_{\triangleq \hat{C}} \underbrace{\left( \text{Id}_{|\hat{S}|} - \gamma \nabla_{\hat{S}, \hat{S}}^2 f(\hat{\beta}) \right)}_{\triangleq \hat{D}} . \end{aligned}$$

- Using the last two points, the goal is to bound the difference between the exact hypergradient and the approximate hypergradient,  $\|\nabla \mathcal{L}(\lambda) - h\|$ . Following Algorithm 5, the exact hypergradient reads

$$\nabla \mathcal{L}(\lambda) = \hat{B} \hat{v} + \hat{\mathcal{J}}_{\hat{S}^c}^\top \nabla_{\hat{S}^c} \mathcal{C}(\hat{\beta}) ,$$

and similarly for the approximate versions

$$h = B v + \mathcal{J}_{\hat{S}^c}^\top \nabla_{\hat{S}^c} \mathcal{C}(\beta) ,$$

with

$$\begin{aligned} B &\triangleq \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(\beta - \gamma \nabla f(\beta))_{\hat{S}^c} - \gamma \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\beta - \gamma \nabla f(\beta))_{\hat{S}} \odot \left( \nabla_{\hat{S}, \hat{S}^c}^2 f(\beta) \right) \hat{\mathcal{J}}_{\hat{S}^c} , \\ \hat{B} &\triangleq \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{\beta} - \gamma \nabla f(\hat{\beta}))_{\hat{S}^c} \\ &\quad - \gamma \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{\beta} - \gamma \nabla f(\hat{\beta}))_{\hat{S}} \odot \left( \nabla_{\hat{S}, \hat{S}^c}^2 f(\hat{\beta}) \right) \hat{\mathcal{J}}_{\hat{S}^c} . \end{aligned}$$

We can exploit these decompositions to bound the difference between the exact hypergradient and the approximate hypergradient

$$\begin{aligned}
 \|\nabla\mathcal{L}(\lambda) - h\| &= \|\hat{B}\hat{v} - Bv + \hat{\mathcal{J}}_{\hat{\mathcal{S}}^c}^\top \nabla_{\hat{\mathcal{S}}^c} \mathcal{C}(\hat{\beta}) - \hat{\mathcal{J}}_{\hat{\mathcal{S}}^c}^\top \nabla_{\hat{\mathcal{S}}^c} \mathcal{C}(\beta)\| \\
 &\leq \|\hat{B}\hat{v} - Bv\| + \|\hat{\mathcal{J}}_{\hat{\mathcal{S}}^c}^\top \nabla_{\hat{\mathcal{S}}^c} \mathcal{C}(\hat{\beta}) - \hat{\mathcal{J}}_{\hat{\mathcal{S}}^c}^\top \nabla_{\hat{\mathcal{S}}^c} \mathcal{C}(\beta)\| \\
 &\leq \|\hat{B}\hat{v} - B\hat{v} + B\hat{v} - Bv\| + \|\hat{\mathcal{J}}_{\hat{\mathcal{S}}^c}^\top (\nabla_{\hat{\mathcal{S}}^c} \mathcal{C}(\hat{\beta}) - \nabla_{\hat{\mathcal{S}}^c} \mathcal{C}(\beta))\| \\
 &\leq \|\hat{v}\| \cdot \|\hat{B} - B\| + \|B\| \cdot \|\hat{v} - v\| + L_{\mathcal{C}} \|\hat{\mathcal{J}}_{\hat{\mathcal{S}}^c}^\top\| \cdot \|\beta - \hat{\beta}\| . \quad (30)
 \end{aligned}$$

Bounding  $\|\hat{v} - v\|$  and  $\|\hat{B} - B\|$  in Equation (30) yields the desired result which is bounding the difference between the exact hypergradient and the approximate hypergradient  $\|\nabla\mathcal{L}(\lambda) - h\|$ .

*Bound on  $\|\hat{v} - v\|$ .* We first prove that  $\|A - \hat{A}\| = \mathcal{O}(\epsilon)$ . Let  $L_H$  be the Lipschitz constant of the application  $\beta \mapsto \nabla^2 f(\beta)$ , then we have

$$\begin{aligned}
 \|A - \hat{A}\|_2 &= \|CD - \hat{C}\hat{D}\|_2 \\
 &\leq \|CD - C\hat{D}\|_2 + \|C\hat{D} - \hat{C}\hat{D}\|_2 \\
 &\leq \underbrace{\|C\|_2}_{\leq 1 \text{ (non-expansiveness)}} \underbrace{\|D - \hat{D}\|_2}_{\leq L_H \|\beta - \hat{\beta}\| \text{ using (H5)}} + \underbrace{\|\hat{D}\|_2}_{\leq 1} \underbrace{\|C - \hat{C}\|_2}_{\mathcal{O}(\|\beta - \hat{\beta}\|) \text{ using (H4)}} \\
 &\leq L_H \|\beta - \hat{\beta}\| + \mathcal{O}(\|\beta - \hat{\beta}\|) \\
 &= \mathcal{O}(\|\beta - \hat{\beta}\|) . \quad (31)
 \end{aligned}$$

Let  $\tilde{v}$  be the exact solution of the approximate system  $A^\top \tilde{v} \triangleq \nabla_{\hat{\mathcal{S}}} \mathcal{C}(\beta)$ . The following conditions are met:

- $\hat{v}$  is the exact solution of the exact linear system and  $\tilde{v}$  is the exact solution of the approximate linear system

$$\begin{aligned}
 \hat{A}^\top \hat{v} &\triangleq \nabla_{\hat{\mathcal{S}}} \mathcal{C}(\hat{\beta}) \\
 A^\top \tilde{v} &\triangleq \nabla_{\hat{\mathcal{S}}} \mathcal{C}(\beta) .
 \end{aligned}$$

- One can control the difference between the exact matrix in the linear system  $\hat{A}$  and the approximate matrix  $A$

$$\|A - \hat{A}\|_2 \leq \delta \|\beta - \hat{\beta}\| ,$$

for a certain  $\delta > 0$  (Equation (31)).

- One can control the difference between the two right-hand side of the linear systems

$$\|\nabla_{\hat{\mathcal{S}}} \mathcal{C}(\beta) - \nabla_{\hat{\mathcal{S}}} \mathcal{C}(\hat{\beta})\| \leq L_{\mathcal{C}} \|\beta - \hat{\beta}\| ,$$

since  $\beta \mapsto \nabla \mathcal{C}(\beta)$  is  $L_{\mathcal{C}}$ -Lipschitz continuous (H6).

- One can control the product of the perturbations

$$\delta \cdot \|\beta - \hat{\beta}\| \cdot \|\hat{A}^{-1}\|_2 \leq \rho < 1 \quad .$$

Conditions are met to apply the result by [Higham \(2002, Thm 7.2\)](#), which leads to

$$\begin{aligned} \|\tilde{v} - \hat{v}\| &\leq \frac{\epsilon}{1 - \epsilon\|\hat{A}^{-1}\|\delta} \left( L_C \|\hat{A}^{-1}\| + \|\hat{v}\| \cdot \|\hat{A}^{-1}\|\delta \right) \\ &\leq \frac{\epsilon}{1 - \rho} \left( L_C \|\hat{A}^{-1}\| + \|\hat{v}\| \cdot \|\hat{A}^{-1}\|\delta \right) \\ &= \mathcal{O}(\epsilon) \quad . \end{aligned} \tag{32}$$

The bound on  $\|\tilde{v} - \hat{v}\|$  finally yields a bound on the first quantity in [Equation \(3\)](#),  $\|v - \hat{v}\|$

$$\begin{aligned} \|v - \hat{v}\| &= \|v - \tilde{v} + \tilde{v} - \hat{v}\| \\ &\leq \|v - \tilde{v}\| + \|\tilde{v} - \hat{v}\| \\ &\leq \|A^{-1}A(v - \tilde{v})\| + \|\tilde{v} - \hat{v}\| \\ &\leq \|A^{-1}\|_2 \times \underbrace{\|A(v - \tilde{v})\|}_{\leq \epsilon \text{ (H7)}} + \underbrace{\|\tilde{v} - \hat{v}\|}_{\mathcal{O}(\epsilon) \text{ (Equation (32))}} \\ &= \mathcal{O}(\epsilon) \quad . \end{aligned} \tag{33}$$

*Bound on  $\|B - \hat{B}\|_2$ .* We now bound the second quantity in [Equation \(3\)](#)  $\|B - \hat{B}\|_2$

$$\begin{aligned} \|B - \hat{B}\|_2 &\leq \|\partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(\beta - \gamma \nabla f(\beta))_{\hat{S}} - \partial_\lambda \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{\beta} - \gamma \nabla f(\hat{\beta}))_{\hat{S}}\|_2 \\ &\quad + \gamma \|\partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\hat{\beta} - \gamma \nabla f(\hat{\beta}))_{\hat{S}} \nabla_{\hat{S}, \hat{S}^c}^2 f(\hat{\beta}) \hat{\mathcal{J}}_{\hat{S}^c} - \\ &\quad - \partial_z \text{prox}_{\gamma g(\cdot, \lambda)}(\beta - \gamma \nabla f(\beta))_{\hat{S}} \nabla_{\hat{S}, \hat{S}^c}^2 f(\beta) \hat{\mathcal{J}}_{\hat{S}^c}\|_2 \\ &\leq L_1 \|\beta - \gamma \nabla f(\beta)_{\hat{S}} - \hat{\beta} + \gamma \nabla f(\hat{\beta})\| \text{ using (H4)} \\ &\quad + L_2 \|\hat{\beta} - \beta\| \cdot \|\hat{\mathcal{J}}_{\hat{S}^c}\| \text{ using (H4) and Assumption 6} \\ &= \mathcal{O}(\|\hat{\beta} - \beta\|) \quad . \end{aligned} \tag{34}$$

Plugging [Equations \(33\)](#) and [\(34\)](#) into [Equation \(3\)](#) yields the desired result:  $\|\nabla \mathcal{L}(\lambda) - h\| = \mathcal{O}(\epsilon)$ . ■

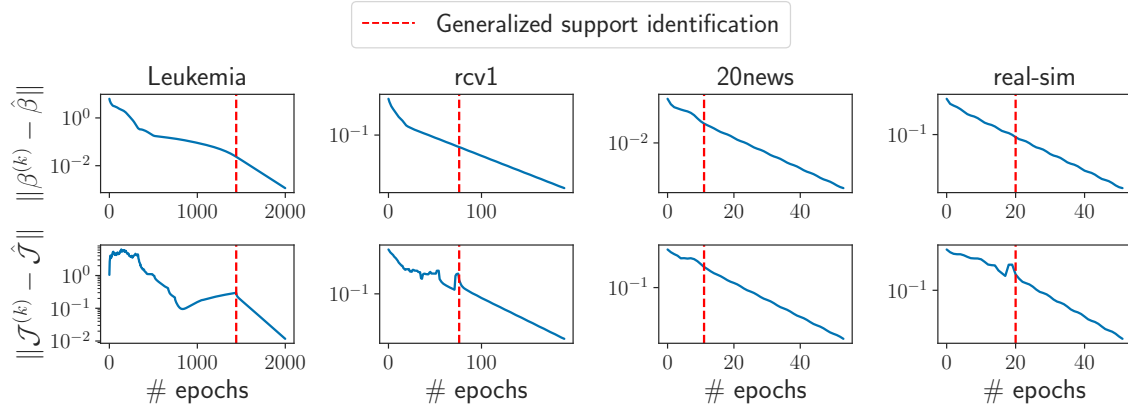


Figure 10: **Local linear convergence of the Jacobian for the Lasso.** Distance to optimum for the coefficients  $\beta$  (top) and the Jacobian  $\mathcal{J}$  (bottom) of the forward-mode differentiation of proximal coordinate descent (Algorithm 3) on multiple data sets.

Table 6: Data set characteristics and regularization parameters used in Figures 3, 10 and 11.

Data sets	<i>leukemia</i>	<i>rcv1</i>	<i>news20</i>	<i>real-sim</i>
# samples	$n = 38$	$n = 20,242$	$n = 19,996$	$n = 72,309$
# features	$p = 7,129$	$p = 19,959$	$p = 632,982$	$p = 20,958$
Lasso	$e^\lambda = 0.01 e^{\lambda_{\max}}$	$e^\lambda = 0.075 e^{\lambda_{\max}}$	$e^\lambda = 0.3 e^{\lambda_{\max}}$	$e^\lambda = 0.1 e^{\lambda_{\max}}$
Logistic regression	$e^\lambda = 0.1 e^{\lambda_{\max}}$	$e^\lambda = 0.25 e^{\lambda_{\max}}$	$e^\lambda = 0.8 e^{\lambda_{\max}}$	$e^\lambda = 0.15 e^{\lambda_{\max}}$
SVM	$e^\lambda = 10^{-5}$	$e^\lambda = 3 \times 10^{-2}$	$e^\lambda = 10^{-3}$	$e^\lambda = 5 \times 10^{-2}$

## D. Additional Experiments

### D.1 Local Linear Convergence

Figures 10 and 11 are the counterparts of Figure 3 for the Lasso and sparse logistic regression. It shows the local linear convergence of the Jacobian for the Lasso, obtained by the forward-mode differentiation of coordinate descent. The solvers used to determine the exact solution up to machine precision are **Celer** (Massias et al., 2018, 2020) for the Lasso and **Blitz** (Johnson and Guestrin, 2015) for the sparse logistic regression. Table 6 summarizes the values of the hyperparameters  $\lambda$  used in Figures 3, 10 and 11.

### D.2 Hypergradient Computation Time

The experimental setting for Figure 12 is the same as for Figure 4, but with a weighted Lasso (i.e.,  $p$  hyperparameters to optimize) as inner problem. It represents the time needed by the different algorithms to compute a single hypergradient as a function of the number

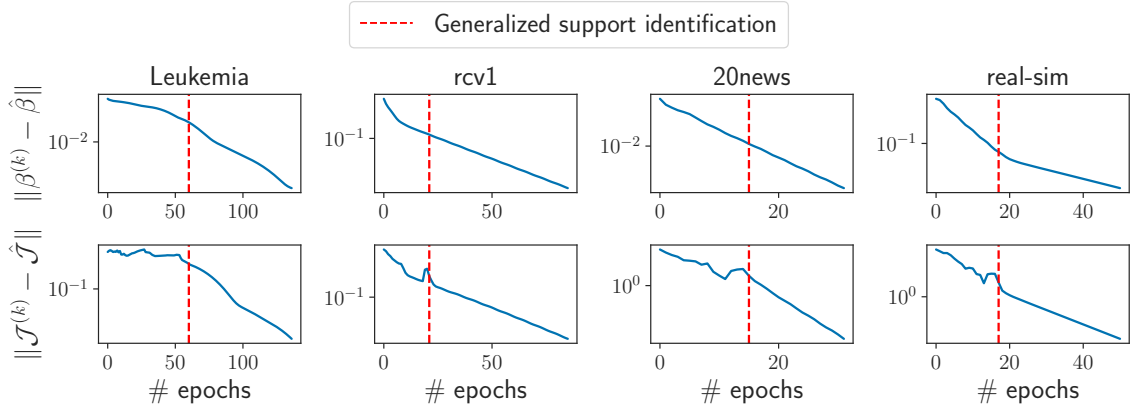


Figure 11: **Local linear convergence of the Jacobian for sparse logistic regression.** Distance to optimum for the coefficients  $\beta$  (top) and the Jacobian  $\mathcal{J}$  (bottom) of the forward-mode differentiation of proximal coordinate descent ([Algorithm 3](#)) on multiple data sets.

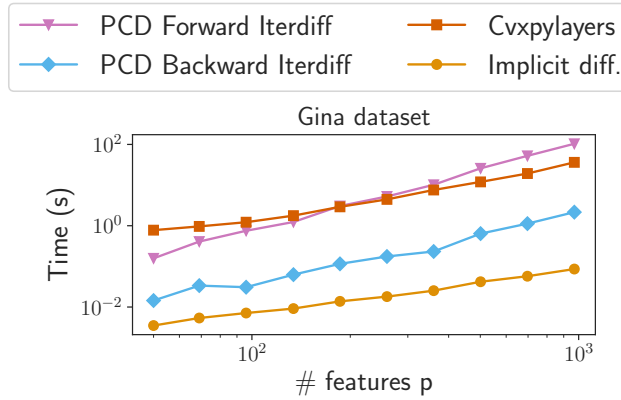


Figure 12: **Weighted Lasso with hold-out criterion.** Time to compute a single hyper-gradient as a function of the number of features on the *gina* data set. The regularization parameters have been chosen uniformly at random in the range  $[0, e_{\max}^{\lambda}]$ .

of features. The regularization amounts were chosen uniformly at random in the interval  $[0, e_{\max}^{\lambda}]$  and each point represents 10 repetitions. [Figure 12](#) shows that when the number of hyperparameters is large the implicit differentiation outperforms the reverse-mode, and the reverse-mode outperforms the forward-mode, by one or more orders of magnitude. This corroborates the complexities summarized in [Table 4](#).